Three Essays In Financial Economics

Inaugural Dissertation to Obtain the Academic Degree of a Doctor in Business Administration at the University of Mannheim

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Chapter 1

Introduction

The events of the global financial crisis of 2007–2009 have moved the issue of financial stability and its implications for the real economy to the center of attention of many researchers in economics and finance. Two financial-stability-related research areas that have gained considerable attention after the crisis are financial shock propagation and amplification mechanisms, and the expectation formation rules of households and financial professionals. The resulting research in these two areas has significantly improved our understanding of how risk arises endogenously in the financial sector and gives plausible explanations for the existence of asset price bubbles and financial cycles. For example, Brunnermeier and Pedersen (2009) and Greenwood et al. (2015a) document novel shock propagation and amplification mechanisms. They demonstrate how even indirect linkages between financial institutions – the interaction between funding and market liquidity, and a high degree of overlap in financial institutions' security portfolios, respectively – imply that an exogenous shock to asset prices can trigger system-wide loss spirals. In the expectation formation literature, empirical evidence that is at odds with the rational expectation assumption has been growing. The empirical evidence suggests that households and financial professionals overweight recent developments (see e.g. Malmendier and Nagel, 2011; Greenwood and Shleifer, 2014; Barberis et al., 2015) and personal experiences (see e.g. Malmendier and Nagel, 2011, 2016; Kuchler and Zafar, 2019).

The aim of this thesis is to contribute to these two research areas. It presents one paper that is predominantly concerned with financial stability, one paper that is concerned with expectation formation and one paper that deals with both research areas. The paper that predominantly focuses on financial stability adopts an theoretical approach and applies methods from agent-based modeling to study how financial regulation affects the resilience of financial institutions. The two papers that deal with expectations adopt an empirical approach and exploit text and survey data, respectively, to study the determinants of the expectations of financial market participants.

This thesis is organized as follows. Chapter 2 presents a paper on the effects of the Liquidity Coverage Ratio (LCR), which is one of the bank liquidity regulations introduced with the international regulatory framework for banks Basel III.[1] It asks whether the regulation increases the banking system's resilience to

[1] The chapter is based on the paper "Evaluating Regulation within an Artificial Financial

exogenous shocks and whether the increased stability comes at the cost of a reduced supply of bank loans to the real sector. These questions are answered with the help of an extensive agent-based model of the financial system, which is introduced in the chapter. The model incorporates the agents, institutional details and shock propagation and amplification mechanisms that were identified as the most important drivers of the built-up of risk within the international financial system before and during the financial crisis of 2007–2009.

The results of Monte Carlo simulations show that the LCR regulation destabilizes the creditors of banks and reduces the supply of bank loans to the real sector. Banks issue less loans to the real sector, because the LCR regulation induces banks to increase their reliance on long-term bond financing, which is associated with lower interest margins. The stability of banks' creditors is lower with the LCR regulation, because they invest a larger share of their balance sheet into banks' long-term debt. Long-term debt, in turn, is more exposed to interest rate and fire sale risk. As a consequence, compared to the scenario without the LCR regulation, banks' creditors suffer larger losses on their bond portfolios when a large negative shock hits the system.

Chapter 3 explores whether systematic over-optimism on the part of bank managers affects the amount of credit that they supply to the real sector.[2] The chapter explains how textual analysis methods can be used to extract a measure of the sentiment of bank managers from bank earnings press release documents. It shows that the resulting measure contains valuable information about the banks that goes beyond the information contained in accounting and macroeconomic variables and defines the information not explained by the accounting and macroeconomic variables as the bank manager sentiment index. The empirical analysis proceeds in two steps. First, it is explored whether the bank manager sentiment index has an extrapolative structure, which implies over-optimism on the part of bank managers. Second, it is analyzed whether the bank manager sentiment index is associated with the investment decisions of banks and their equity investors, whereas the latter has implications for the costs of capital of banks.

The empirical evidence presented in Chapter 3 suggests that systematic over-optimism on the part of banks and their equity investors has real implications. It is documented that banks' decisions on the volume of new loans partially depend on very recent realizations of economic fundamentals, implying that loan growth and economic fundamentals might be systematically disconnected. Furthermore, the chapter presents evidence that suggests that over-optimism on the part of bank managers spills over to their equity investors, who seem to interpret high bank manager sentiment as a positive signal for the risk associated

System – A Framework and its Application to the Liquidity Coverage Ratio Regulation" which is joint work with Jesper Riedler from ZEW Mannheim. The paper was presented at FinMaP-Policy-Clinics in Leuven and Rome, the WEHIA-Conference 2016 in Castellon, the CEF-Conference 2016 in Bordeaux and 2017 in New York, the 25th McKinsey/FIRM Innovation Platform in Frankfurt, the INET-UCT-Workshop 2017 in Oxford, the 2017 Conference on Heterogeneous Agents and Agent-based Modeling: The Intersection of Policy and Research in Washington D.C. and at the Bundesbank research seminar. An earlier version of the paper is available as a ZEW – Centre for European Economic Research Discussion Paper, Riedler and Brueckbauer (2017), and was used by Jesper Riedler as part of his dissertation, Riedler (2017), at Giessen University. Compared to this earlier version, the chapter in this thesis puts a larger emphasis on the application of the model to the evaluation of the LCR evaluation.

[2]The paper, on which this chapter is based, was presented at seminars at the University of Mannheim and ZEW Mannheim.

with bank loan growth. More specifically, higher values of the bank manager sentiment index are associated with a weaker relationship between loan growth rates and the perceived riskiness of banks. The results imply that, for a given loan growth rate, optimistic bank managers face lower costs of capital than pessimistic bank managers, all else equal.

Lastly, Chapter 4 deals with the question of how financial market experts form their stock market expectations.[3] Using an unique survey dataset containing macroeconomic and financial expectations of German financial market experts, the chapter studies three aspects of the experts' DAX forecasts. First, it investigates the sources of the variation in expected DAX returns. It is shown that the financial market experts differ considerably in how they incorporate macroeconomic and financial information into their DAX forecasts. It is found that the experts not only disagree about the importance of macroeconomic and financial state variables for DAX returns, they also disagree about how these variables affect DAX returns. Second, the chapter aims to provide new evidence on the relationship between expected returns and economic conditions. Based on the chapter's main survey measure of expected returns, the results presented are largely consistent with the view that expected returns are counter-cyclical. Finally, the chapter evaluates the accuracy of the financial market experts' DAX return forecasts. It is shown that an aggregated measure of the financial market experts' stock return forecasts has weak predictive power for actual returns, but is a less precise forecast than a simple average of historical stock returns.

[3]The paper, on which this chapter is based, was presented at seminars at the University of Mannheim and ZEW Mannheim and is available as a ZEW – Centre for European Economic Research Discussion Paper, Brückbauer (2020).

Chapter 2

Evaluating Regulation Within An Artificial Financial System - A Framework And Its Application To The Liquidity Coverage Ratio Regulation

2.1 Introduction

Banks suffered multiple runs during the financial crisis of 2007–2009. One run took part on the market for bank loans, when firms became increasingly concerned about their access to bank financing and drew down their credit lines (Ivashina and Scharfstein, 2010). The collapse of Lehman Brothers triggered additional runs by the banks' wholesale debt holders, who were an important source of banks' short-term funding (e.g Brunnermeier, 2009; Gorton and Metrick, 2012a).

These runs had serious economic consequences. As it turned out, the liquidity buffers of many banks were insufficient to cover the outflows of cash. The resulting liquidity problems forced banks to significantly reduce their supply of bank loans to the real sector, which in turn exacerbated the severity of the economic crisis (see e.g. Ivashina and Scharfstein, 2010; Cornett et al., 2011; Dagher and Kazimov, 2015). In order to prevent their banking systems from collapsing, many governments were forced to stabilize their banks. These large scale assistance programs had serious negative consequences for the fiscal positions of governments and paved the way for government debt crisis.

With the aim of improving the resilience of the banking sector and to reduce the need for large scale liquidity assistance in the future, the then existing international regulatory framework for banks was modified and extended after the financial crisis. New liquidity regulations that address the insufficient liquidity management of banks before and during the financial crisis are an integral part of the resulting Basel III regulatory framework. The first Basel III liquidity regulation that was implemented is the Liquidity Coverage Ratio (LCR, henceforth). The LCR regulation forces banks to always hold enough liquidity such that they are expected to be to able to operate 30 days without access to external funding under all conditions. The two components of the ratio are the banks' holdings of High Quality Liquid Assets (HQLA, henceforth) and their expected net cash outflows. Both components are calculated under a hypothetical stress scenario, which, for example, takes into account that market prices of otherwise liquid assets can become depressed and that banks might lose access to short-term debt markets.

In this paper, we study the impact of the LCR on the stability of banks and the supply of bank loans to the real sector. We ask how effective the regulation is in stabilizing banks when there is a confidence crisis similar to that experienced by banks during the financial crisis of 2007–2009. Banks have several possibilities to comply with the regulation and, given their diverse business models, may respond differently to the new restrictions they face.[1] Taking this heterogeneity in behavioral responses into consideration, we explore whether and under which conditions the regulation has unintended consequences that need to be addressed by policy makers and regulators.

We aim to answer our research questions by developing a new, dynamic agent-based model of the financial system.[2] We have chosen the agent-based approach over the traditional equilibrium approach, because the agent-based approach does not face a trade-off between mathematical traceability and modeling choices (Farmer and Geanakoplos, 2009). For example, most standard theoretical dynamic models with a financial sector can only be solved by linearization around the model economy's steady state (e.g. Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997). The propagation of financial stress, however, is inherently non-linear. A recent important contribution to this literature is Brunnermeier and Sannikov (2014) who use continuous-time methods that allow for the inclusion of some important non-linear features into equilibrium models with a financial sector. However, in our opinion, these models do not yet

[1]They may substitute illiquid assets (i.e. loans) with HQLA, leaving their funding structure unchanged. This strategy would likely cause an overall reduction in lending to the real sector. Banks may also reduce their net outflows, by either reducing the maturity mismatch between assets and liabilities or by switching to funding sources that are deemed more stable. The implications of the latter strategy are unknown ex ante.

[2]We choose the theoretical approach over an empirical approach because an empirical evaluation of the LCR faces several obstacles at once. Given that the regulation has been gradually phased in as late as 2015, the first obstacle is an insufficient number of observations, and the absence of data on some important variables. The second obstacle is identification. First, the LCR regulation has been introduced simultaneously with several other regulations that have fundamentally changed the trade-offs that banks face in setting their asset-liability structure. Another complication has been the low interest environment: low opportunity costs of holding central bank reserves and cash, which are important components of High Quality Liquid Assets, might have lead to adjustment behaviors that may not be viable in the long run. These confounding factors make it, at least in our opinion, impossible to isolate the causal effect of the LCR regulation. Moreover, an empirical analysis may only capture adjustment behavior that is not fully informative about the regulation's long-term effects.

allow for the evaluation of regulations in a realistic setting, which includes all the necessary details of the institutional environment banks and other financial institutions are embedded in, and all the necessary details of the regulations we want to study.

The model itself constitutes our second contribution to the literature. The concepts we propose allow for a rich bank balance sheet structure that includes assets of differing maturity and liquidity as well as diverse debt forms such as short and long-term, secured and unsecured funding instruments. The introduction of these details enables us to capture the effects of the LCR that go beyond the substitution of illiquid loans with liquid assets. For example, banks in our model may increase their LCR by switching to long-term funding or by increasing the quality of collateral in secured funding transactions. Thanks to its general structure, the model can be quickly adapted to address a variety of questions concerning e.g. financial stability, expectations formation, asset prices or monetary policy transmission.

The developments before and during the financial crisis serve as a rough guide to our modeling choices with regard to the relevant agents and institutions in our model. At its core is a banking market, which is populated by two types of agents: commercial and investment banks. Commercial banks follow a traditional business model, i.e. they take in deposits and issue loans to the non-financial sector, thereby connecting the banking market to an exogenous real sector. The only liquid asset available to commercial banks is cash which does not pay any interest. Since they have more lending opportunities than deposits, commercial banks also finance loans with overnight and long-term wholesale debt provided by the investment banks. The investment bank agents in our model are best described as shadow banks (i.e. dealer banks, SPVs, money market funds) who finance investments in liquid securities and interbank loans via a mix of market-based funding instruments and unsecured wholesale funding. The inclusion of investment banks is motivated by the fact that large broker dealer and investment banks were at the core of the financial crisis. As their empirical counterparts, their highly overlapping portfolios (e.g. Blei and Ergashev, 2014) and their prevailing short-term funding sources (e.g. Adrian and Shin, 2010; Gorton and Metrick, 2012a) render the investment bank agents in our model a catalyst for financial stress.

Our results suggest novel impact channels and are largely confirmed by empirical evidence. Specifically, we find that the LCR regulation will reduce loans to the real sector, increase long-term interest rates and diminish the role of the overnight interbank market as a source of funding. In our analysis of financial stability, we focus on the implications of the LCR for commercial banks' loan supply to the real sector. Emulating the loss of confidence banks experienced after the collapse of Lehman Brothers in September 2008, we find that the LCR regulation is unlikely to stabilize the loan supply. On the contrary, when the LCR regulation is binding, a strong confidence shock can lead to a protracted credit crunch by destabilizing the creditors of banks. The mechanism behind this result is the following: through its incentives for long-term funding sources, the share of interbank debt subject to mark-to-market accounting on the balance sheets of investment banks increases under the LCR. When the confidence crisis hits, fire sales of these assets produce losses for investment banks that are significantly larger than those in the scenario without the LCR. Weakened investment banks then supply less wholesale debt at higher interest rates to commercial banks. Lower profitability and smaller balance sheets of commercial banks produce the adverse effects on the supply of loans under the LCR. To the best of our knowledge, our result that the LCR increases fire sale risk for those who lend to banks is new to the literature.

The rest of the paper is organized as follows. Section 2.2 gives an overview of the literature related to our paper. Section 2.3 introduces the model. Section 2.7 explains how the banks in our model integrate the restrictions of the LCR into their decision making rules. Section 2.8 presents the results of the Monte Carlo simulations. Section 2.9 summarizes and concludes.

2.2 Related Literature

Our paper contributes to the small but growing literature on the dynamic effects of bank liquidity regulations.[3] De Nicolo et al. (2014); Hugonnier and Morellec (2017) study the impact of microprudential liquidity and capital restrictions in dynamic models of banks. Compared to a scenario with capital requirements alone, De Nicolo et al. (2014) find that the introduction of liquidity requirements significantly reduces the ability of banks to carry out maturity transformation, resulting in a lower levels of bank lending and welfare. Hugonnier and Morellec (2017) study the endogenous responses of banks to the introduction of liquidity and leverage requirements. They find that the introduction of liquidity requirements raises the likelihood of defaults but leads to lower losses given a default. However, Hugonnier and Morellec (2017) also show that if liquidity requirements are complemented by leverage requirements, both the likelihood of default and the losses given default decrease. Bech and Keister (2017); Erol and Ordoñez (2017) are concerned with the theoretical implications of liquidity regulations for interbank market outcomes. Bech and Keister (2017) use a model of monetary policy implementation to study the impact of the LCR on interbank interest rates. They find that, depending on the amount of reserves and HQLA in the system, the LCR can have a negative effect on overnight interest rates and a positive effect on long-term interbank rates, thereby distorting monetary policy transmission. Their result is generated by the fact that only long-term but not overnight interbank loans help banks to fulfill their liquidity requirements. Banks may thus demand less of the former and more of the latter. Erol and Ordoñez (2017) deploy an network model to study the impact of liquidity regulations on the interbank network structure. In their model, banks endogenously determine the optimal number of counterparties, each of which provides insurance against refinancing shocks. The authors find that there is a critical threshold above which higher liquidity regulations lead to an abrupt decrease in the number of interbank relationships, resulting in higher levels of systemic risk in the banking system.

Despite the low data availability, there are a few papers that present empirical evidence on the effects of bank liquidity regulations. Bonner and Eijffinger (2016), for example, study the impact of the Dutch quantitative liquidity requirement on interbank markets and monetary policy implementation. They find that for banks that are below their own liquidity targets, the volume of

[3] The majority of studies in the literature on bank liquidity requirements are concerned with the questions of whether and how such requirements can stabilize banks. See e.g. Diamond and Kashyap (2016) for a recent overview.

long-term interbank borrowing increases substantially. Moreover, for banks below their liquidity thresholds, interest rates for lending and borrowing on the interbank market were significantly higher. Banerjee and Mio (2017) empirically investigate the responses of UK banks to the introduction of the Individual Liquidity Guidance regulation in 2010. The authors find that banks subject to the regulation substituted short-term interbank loans with HQLA and replaced short-term wholesale borrowings by retail deposits. They do not find that the liquidity regulation had a negative effect on the supply of bank loans to the non-financial sector. Roberts et al. (2018) exploit that the LCR was only introduced for large banks in the USA in 2013. Using a difference-in-difference approach, they find that after the introduction of the LCR large banks have decreased the liquidity mismatch between their assets and liabilities, have reduced lending to the real sector, and have become more resilient in terms of fire-sale risk and complexity relative to small banks that are not subject to the LCR.

Our paper is also related to the strands of literature that study the theory of financial shock propagation. Shocks can propagate directly through creditor-debtor relationships on the interbank market or, in combination with fire sales, indirectly through overlapping portfolios.[4] In particular, the literature on interbank networks has flourished in the wake of the financial crisis. The general network structure, the size of shocks, the location of the shocked node in the network and the capital structure of the banks linked within the interbank market have been found to be crucial for the susceptibility of the banking system to systemic risk.[5] However, most network models in the literature comprise of a static structure in which banks do not actively manage their balance sheets. Our paper, on the other hand, is more related to a small but burgeoning literature which model banks as agents that can in one form or the other react to changing circumstances. The behavior of agents thereby changes the dynamics of shock propagation. One of the first models in this spirit is developed by Bluhm and Krahnen (2014). They study a system of three financial institutions that are connected through direct interbank linkages and indirect linkages due to overlapping portfolios. Prices are computed endogenously, which can lead to fire sale dynamics, as institutions, which need to fulfill capital requirements, adjust their portfolios in response to a shock. In Georg (2013), banks optimize their portfolio consisting of a risky asset and riskless excess reserves. They fund their asset side with equity, deposits, interbank loans and central bank loans. The volume of deposits and the return on the risky asset fluctuate randomly, which triggers reactions from banks. The framework is employed in order to compare different network structures with regard to their effect on stability. According to Georg (2013), contagion tends to be less pronounced in scale-free interbank networks than in random and small-world networks. In Fischer and Riedler (2014), financial institutions optimize a portfolio consisting of a risky asset and cash. The price of the risky asset is determined endogenously through market clearing and thus depends on the expectations of agents. Depending on their past success, agents can follow either a fundamentalist or a chartist strategy when forming expectations. Within this framework, it is shown that

[4] Seminal contributions to the literature on direct linkages include Allen and Gale (2000); Freixas et al. (2000); Eisenberg and Noe (2001). Fire-sale-driven shock propagation is discussed e.g. in Shleifer and Vishny (1992); Kiyotaki and Moore (1997); Brunnermeier and Pedersen (2009).

[5] For a survey of the literature see e.g. Chinazzi and Fagiolo (2013).

when leverage is high and funding short-term, overlapping portfolios become a major source of systemic risk. Greenwood et al. (2015b) construct a model of fire-sale spillovers that can be estimated with balance sheet data. A bank in their model adjusts its balance sheet according to a specified rule when it is hit by an adverse shock. The adjustment leads to price impacts, which may induce other banks to react. Duarte and Eisenbach (2015) extend this framework in order to build a systemic risk measure that can track vulnerabilities over time. They calibrate their model on U.S. broker-dealers, using data from the tri-party repo market. The calibrated model documents a buildup of systemic risk starting in the early 2000s. Furthermore, it can be inferred that during the financial crisis an exogenous 1 percent decline in the prices of repo-financed assets would have led to fire sales resulting in a 12 percent drop in broker-dealers' equity. Halaj and Kok (2015) present a model, in which the interbank network emerges endogenously from agents' portfolio optimization. Since regulation imposes constraints on the portfolio decisions of agents, the authors can use their model in order to assess the impact of different regulatory measures on the structure of the interbank market and the implied contagion risk. Their findings suggest that while large exposure limits do have a pronounced effect on contagion risk, credit valuation adjustments are less effective. Aldasoro et al. (2015) develop a network model in which banks lend to each other in the interbank market and invest in non-liquid assets. While aggregate positions of interbank assets on balance sheets are the result of portfolio-optimization and market clearing, specific interbank linkages are generated via matching algorithms. When testing the impact of liquidity and capital requirements on their model, they find that although both types of regulation effectively reduce systemic risk, capital requirements result to be less detrimental to overall investment. Montagna and Kok (2016) develop an agent-based model, where agents interact with each other through a multi-layered network model. The linkages of different layers of the model thereby represent interbank relationships of different maturities as well as indirect linkages through portfolio overlap. In their model, banks adjust their balance sheets only when regulatory requirements are violated. The authors find that including the multiple layers of linkages non-linearly amplifies the propagation of shocks.

2.3 Model Overview

The model, schematized in Figure 2.1, comprises three types of markets: asset markets, funding markets and a banking market. The banking market is populated by heterogeneous agents that can be classified as either commercial bank agents (cb-agents) or investment bank agents (ib-agents). Interactions between the two bank business models are confined to two wholesale debt markets: an overnight loan market and a bond market. In our model, and broadly in line with empirical evidence (see e.g. Craig and Von Peter, 2014), a few large ib-agents at the core provide interbank loans to smaller cb-agents in the periphery of the banking market. Cb-agents take customer deposits and issue loans to the real sector. Besides using deposits, they can finance their activities through equity and the two types of wholesale debt. An exogenous central bank acts as a lender of last resort by providing limitless credit to cb-agents at a relative expensive marginal lending rate. Ib-agents, in contrast, provide overnight interbank

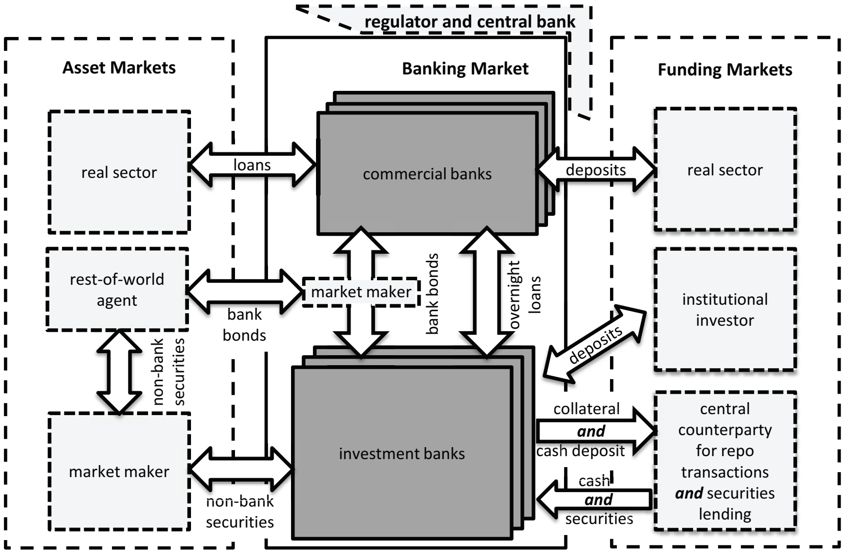


Figure 2.1: Model setup

loans, underwrite as well as trade bank bonds and trade non-bank securities on secondary asset markets. An exogenous market maker adjusts the prices of non-bank securities and bank bonds taking into account excess demand for these assets. While investment banks' demand is the sole driver of asset prices in normal times, a highly risk averse rest-of-world agent steps in to buy bank bonds and non-bank securities on the secondary market in a crisis. For funding, ib-agents rely on equity, unsecured (run prone) deposits from exogenous institutional investors, short sales and repurchase agreements (repos). An exogenous central counterparty agent facilitates the investment banks' repo transactions and short sales by lending cash and securities. Although ib-agents in our model do not directly lend to each other, they are indirectly interconnected through overlapping portfolios. Given the features of their business model, these agents may also represent financial institutions that are classified as shadow banks (e.g. hedge funds, money market funds, structured investment vehicles etc.).

2.4 Modeling Commercial Banks

This section describes the properties and behavioral rules of cb-agents. Section 2.4.1 introduces the laws of motion of all balance sheet variables. The order in which these laws are presented correspond to the timing in the model. Section 2.4.2 presents the asset side management decisions that cb-agents take. Their decisions on the volume of loans and cash holdings determine the size of their balance sheet and the volume of wholesale debt that has to be raised on the interbank market. After having determined the volume of wholesale debt, cb-agents have to decide on its maturity structure. Section 2.4.3 describes how cb-agents tackle this problem. Before cb-agents can raise their desired volume of overnight debt on the interbank market, they have to determine how much debt they will raise from which counterparties. Section 2.4.4 presents the respective decision rules. Finally, the basis for all these decisions are the expectations that cb-agents have formed with respect to all the relevant variables. How cb-agents form their expectations is presented in Section 2.4.5.

2.4.1 Balance Sheet

The balance sheet of cb-agent $c \in \{1, 2, ..., n^C\}$ at the end of period t has the following structure

Assets	Liabilities
Loans, $L_{c,t}$	Deposits, $D_{c,t}$
Cash, $C_{c,t}$	$\left.\begin{array}{l}\text{Overnight Debt, } I_{c,t} \\ \text{Long-term Debt, } B_{c,t}\end{array}\right\} W_{c,t}$
	Equity, $E_{c,t}$

with $W_{c,t}$ denoting wholesale debt. It is important to consider the sequence of events in the model to derive the laws of motion of the balance sheet variables. Each period starts with the registration of defaults on loans and changes to deposits. To simplify matters, we assume that they occur overnight, i.e. between the end of period $t-1$ and the beginning of period t. Agents pay and receive interest as well as principal payments at the beginning of a period. The first decision entails the appropriation of profits that have accrued overnight. Decisions on the issuance of new loans and desired cash holdings follow. Lastly, agents raise funds on wholesale debt markets in order to equilibrate the asset and liability side of their balance sheets.

The profit of cb-agent c in period t is computed from the difference between interest payments on loans and the last period's funding costs:

$$\Pi_{c,t} = L_{c,t-1} r^L_{c,t} - D_{c,t-1} r^D_{c,t-1} - B_{c,t-1} \bar{r}^B_{c,t-1} - I_{c,t-1} \bar{r}^I_{c,t-1}, \tag{2.1}$$

with $r^D_{c,t}$ being the interest rate paid to depositors, $\bar{r}^B_{c,t}$ the average interest rate paid on long-term wholesale debt and $\bar{r}^I_{c,t}$ the average interest rate paid on overnight loans. The latter also includes the cost of borrowing from the central bank. The effective return on loans $r^L_{c,t} = (1 - \rho^L_{c,t}) \tilde{r}^L_{c,t-1} - \rho^L_{c,t}$ is a function of two exogenously set rates: the charged interest rate $\tilde{r}^L_{c,t-1}$ and the realization of the stochastic loan default rate $\rho^L_{c,t}$.

The decision on the appropriation of realized profits follows a simple rule: We assume that cb-agents have an exogenously defined equity target E^*_c and that they cannot raise new equity from outside sources. As a consequence, any profit $\Pi_{c,t}$ that would lead to equity above the target is paid out as a dividend $Div_{c,t}$:[6]

$$\begin{aligned} E_{c,t} &= \min\{E^*_c, E_{c,t-1} + \Pi_{c,t}\}, \\ Div_{c,t} &= \max\{0, E_{c,t-1} + \Pi_{c,t} - E_{c,t}\} \end{aligned} \tag{2.2}$$

The difference between profit and dividends is retained earnings, i.e. $\Delta\Pi_{c,t} = \Pi_{c,t} - Div_{c,t}$. According to the timing of the model explained above, retained

[6]Our heuristic for the payout management of bank agents is supported by empirical evidence. Adrian et al. (2015) e.g. find that financial institutions adjust payouts in order to achieve a desired path for equity. Furthermore, in times of financial stress it can be rather difficult or undesirable to raise equity capital.

earnings, changes to deposits, incoming and outgoing debt payments change the cash holdings before any asset side decisions are considered by cb-agents. Taking this into account, we define an intermediate measure for cash holdings:

$$C'_{c,t} = C_{c,t-1} + \Delta\Pi_{c,t} + \Delta D_{c,t} + (1-\rho^L_{c,t})(1-m_L)L_{c,t-1} - (1-m_B)B_{c,t-1} - I_{c,t-1}, \tag{2.3}$$

with $\Delta D_{c,t}$ being a stochastic change in customer deposits and $(1 - m_L)$ and $(1 - m_B)$ defining the repayment rates for performing loans and bank bonds, respectively. The parameters $\{m_L, m_B\} \in [0, 1]$ can be interpreted as maturity parameters.[7]

Changes to cb-agents' cash and loan positions are subject to their decisions $\Delta C_{c,t}$ and $\Delta L_{c,t}$, which are described in the next section. The respective laws of motion therefore amount to

$$C_{c,t} = C'_{c,t} + \Delta C_{c,t} \tag{2.4}$$

and

$$L_{c,t} = m_L L_{c,t-1}(1 - \rho^L_{c,t}) + \Delta L_{c,t}. \tag{2.5}$$

The volume of wholesale debt required by bank c is the residual between its assets and the volume of deposits and equity:

$$W_{c,t} = W_{c,t-1} + \Delta W_{c,t} = L_{c,t} + C_{c,t} - E_{c,t} - D_{c,t} \tag{2.6}$$

The funding decision a cb-agent faces (derived in Section 2.4.3) concerns the composition of wholesale debt rather than its volume. Specifically, each agent will have to choose the fraction $a_{c,t}$ of wholesale debt to be borrowed in long-term bank bonds, i.e.

$$B_{c,t} = a_{c,t}W_{c,t} \quad \text{and} \quad I_{c,t} = (1 - a_{c,t})W_{c,t}. \tag{2.7}$$

Both overnight and long-term debt will be raised from investment banks (agents $i \in \{1, 2, ..., n^I\}$), or - in the case of a shortage of credit supply - from the lender of last resort (agent LLR). For the sake of simplicity, we assume that funds from the central bank also need to be rolled over each period. We can therefore define the total volume of overnight debt as the sum of overnight interbank loans and funds from the central bank: $I_{c,t} = I_{c,LLR,t} + \sum_{i=1}^{n^I} I_{c,i,t}$.

2.4.2 Asset Side Management

When deciding on the issuance of new loans $\Delta L_{c,t}$ to the real sector, cb-agents first check if the expected return on the loans $\mathrm{E}_{c,t}[r^L]$ exceeds the expected marginal wholesale refinancing costs $\mathrm{E}_{c,t}[r^{\Delta W}]$.[8] If this is the case, the agent

[7] For example, $\{m_L, m_B\} = 0$ implies that debtors need to repay all credit every period, while $\{m_L, m_B\} = 1$ implies that the principal of loans is never to be paid back. In reality, loans to the real sector and long-term bank bonds typically do not exhibit constant repayment rates. However, when interpreting $L_{c,t}$ and $B_{c,t}$ as portfolios of loans and debt contracts, the modeling choice becomes more realistic. When comparing the maturity profile implied by the constant repayment rates to bank balance sheet data, our model slightly underestimates the fraction of short-term loans and short-term debt to overall loans and wholesale debt.

[8] $\mathrm{E}_{c,t}[\cdot]$ denotes the expectations operator, with the subindices defining by whom and in what period expectations are formed.

computes an upper bound for new loan issuances $\Delta L_{c,t}^{risk}$ by employing a value-at-risk approach.[9] The bound seeks to ensure that the bank's equity is sufficient to absorb losses from defaults on loans and variations in refinancing costs. More specifically, risk management allows the issuance of new loans until the bank's total value at risk is equal to its equity, i.e. $\Delta L_{c,t}^{risk} = VaR_t^{-1}(-E_{c,t})$. Total value at risk is thereby computed as the sum of the individual values at risk with confidence level x^L from outstanding loans VaR_{out}, prospective loans $VaR_t^{prosp}(\Delta L)$ and wholesale refinancing costs $VaR_t^{ref}(\Delta L, \Delta C)$. The volume of new loans is additionally constrained from above by a precautionary limit $\Delta L_{c,t}^{prec} := (1 - m_L)L_{c,t-1} + E_{c,t}$, which is put in place to inhibit an excessively rapid build up of the loan portfolio.[10] The volume of new loans is thus given by:

$$\Delta L_{c,t} = \begin{cases} \min(\Delta L_{c,t}^{risk}, \Delta L_{c,t}^{prec}) & \text{if} \quad \mathrm{E}_{c,t}[r^L] \geq \mathrm{E}_{c,t}[r^{\Delta W}] \\ 0 & \text{if} \quad \mathrm{E}_{c,t}[r^L] < \mathrm{E}_{c,t}[r^{\Delta W}]. \end{cases} \tag{2.8}$$

In the context of our baseline model, there is no intrinsic reason for cb-agents to hold cash at the end of a period.[11] In order to minimize their need for external funding, agents will try to get rid of their intermediate cash holdings defined in Eq. 2.3. However, when agents want to deleverage faster than the maturity structure of its debt permits, cash positions will inevitably be positive. Since the maturity of bank bonds imposes a lower bound to the wholesale debt volume (i.e. $W_{c,t-1} + \Delta W_{c,t} \geq m_B B_{c,t-1}$), the deleveraging bound for changes in cash amounts to $\Delta C_{c,t}^{del}(L) = m_B B_{c,t-1} + D_{c,t} + E_{c,t} - C'_{c,t} - L$. Taking this into account, $\Delta C_{c,t} = \max\{-C'_{c,t}, \Delta C_{c,t}^{del}\}$.

2.4.3 Liability Side Management

The total volume of wholesale debt to be raised by a cb-agent is determined by their asset side management and the law of motion specified in Eq. (2.6). To compute new issues of bank bonds $\Delta B_{c,t} = B_{c,t} - m_B B_{c,t-1}$, agents have to decide what proportion $a_{c,t} \in [0, 1]$ of their wholesale debt $W_{c,t}$ should be borrowed in bank bonds $B_{c,t} = a_{c,t} W_{c,t}$. They do this by taking into account the trade-off between funding costs and funding stability that arises from the difference in maturity between overnight interbank loans and bank bonds. While all interbank loans mature overnight, only a fraction $(1 - m_B)$ of bank bonds need to be refinanced at the current interest rate. The higher funding stability of bonds comes at the cost of a term premium, which is an emergent property of the model. We model the trade-off through a mean-variance optimization of the expected interest rate surplus in the next period $S_{c,t+1}$ per unit of outstanding loans this period. The targeted optimal share of long-term debt thus follows

[9] The values at risk are computed through Monte Carlo simulations described in Appendix 2.10.2. Although such simulations increase computation time, they allow us to include realistic assumptions about the stochastic process of loan defaults into the risk management of agents. An analytical derivation of the loss distribution under realistic assumptions is often not possible.

[10] Since loan demand is perfectly elastic, cb-agents could theoretically issue as many new loans as they wish. However, since market conditions may unexpectedly change in the near future, rapid buildups of loan portfolios are very risky for cb-agents. Consistent with our assumption, large jumps in the volume of bank loans are very rare in reality.

[11] When introducing the liquidity coverage ratio in Section 2.7 this assumption will be revised.

from the following optimization problem:[12]

$$a_{c,t}^{*} = \arg\max_{a} \left(\mathrm{E}_{c,t}[S_{t+1}] - 0.5\lambda_{c,t} \mathrm{Var}_{c,t}(S_{t+1}) \right), \tag{2.9}$$

with $\lambda_{c,t}$ being a time-variant scaling factor[13] and

$$S_{c,t+1} = r_{c,t+1}^{L} - \frac{W_{c,t}}{L_{c,t}} \left(a_{c,t} \bar{r}_{c,t+1}^{B} + (1 - a_{c,t}) \bar{r}_{c,t+1}^{I} \right). \tag{2.10}$$

The average overnight interest rate $\bar{r}_{c,t}^{I}$ and the average bank bond interest rate $\bar{r}_{c,t}^{B}$ are calculated as follows:

$$\bar{r}_{c,t}^{I} = (1 - a_{c,t}^{LLR}) \frac{\sum_{i=1}^{n^I} I_{c,i,t} r_{i,c,t}^{I}}{\sum_{i=1}^{n^I} I_{c,i,t}} + a_{c,t}^{LLR} r_{t}^{LLR} \tag{2.11}$$

and

$$\bar{r}_{c,t}^{B} = \frac{m_B B_{c,t-1} \bar{r}_{c,t-1}^{B} + \Delta B_{c,t} r_{c,t}^{B}}{B_{c,t}}, \tag{2.12}$$

with $I_{c,i,t}$ denoting the volume of overnight debt borrowed from ib-agent i, $r_{i,c,t}^{I}$ being the interest rate charged by that agent and $a_{c,t}^{LLR} = I_{c,LLR,t}/I_{c,t}$ defining the fraction of overnight debt borrowed by cb-agent c from the central bank (lender of last resort) at the exogenous marginal lending facility rate r_{t}^{LLR}.

The volume of bank bonds on a cb-agent's balance sheet is constrained by investor demand of bonds and by the maturity of outstanding bonds.[14] The two constraints translate into an upper and lower bound for the fraction of long-term wholesale debt, i.e. $a_{c,t} = \min\{\max\{a_{c,t}^{*}, a_{c,t}^{\mathrm{dem}}\}, a_{c,t}^{mat}\}$. The investor demand induced upper bound is computed as follows: $a_{c,t}^{\mathrm{dem}} = \sum_{i=1}^{n^I} (m_B B_{c,t-1} + \Delta B_{i,c,t} - B_{c,t-1}^{MM})/W_{c,t}$, with $\Delta B_{i,c,t}$ being the excess supply of long-term funding from ib-agent i to cb-agent c and $B_{c,t-1}^{MM}$ being the value of the market makers inventory of loans to that commercial bank. The maturity induced lower bound amounts to $a_{c,t}^{mat} = m_B B_{c,t-1}/W_{c,t}$.

2.4.4 Raising Overnight Interbank Debt

Once the demand for overnight interbank loans $I_{c,t} = (1 - a_{c,t})W_{c,t}$ is known to the cb-agent, it needs to raise these funds on the interbank market. This involves two steps: First, loan offers from all n^I ib-agents and the central bank are collected and evaluated. The central bank acts as a lender of last resort (i.e. $I_{LLR,c,t} = \infty$) and ensures that sufficient funding is available to cb-agents. Second, starting with the best offer, agents engage in bilateral transactions until their demand for overnight interbank funding is completely satisfied. We assume

[12] See Appendix 2.10.3 for the derivation of $a_{c,t}^{*}$

[13] In a mean-variance optimization setup, λ would typically be a risk aversion parameter. However, in our context it makes sense to define λ as a variable scaling factor. This will allow us to calibrate the trade-off between funding costs and funding stability along the lines of the following statement: if the probability that overnight funding costs exceed long-term funding costs is smaller than x percent, then wholesale debt should be exclusively overnight.

[14] We assume that cb-agents cannot buy back their bonds.

that an offer is evaluated according to two factors: the trust $v_{c,i,t}$ between cb-agent c and ib-agent i, which is a measure of the frequency of past transactions, and the relative funding costs $u_{c,i,t}$.[15] The two factors are evaluated jointly via a Cobb-Douglas function $U^C_{c,i,t} = (v_{c,i,t})^{\gamma_v}(u_{c,i,t})^{\gamma_u}$, with the exponents γ_v and γ_u being the valuation elasticities of the two factors. The definitions of the trust measure $v_{c,i,t}$ and the measure of relative funding cost $u_{c,i,t}$, as well as the formal description of the procedure that leads from the valuation of an interbank loan offer $U^C_{c,i,t}$ to an actual interbank loan on balance sheet $I_{i,c,t}$ is given in Appendix 2.10.4.

2.4.5 Expectation Formation

In order to successfully manage their assets and liabilities, cb-agents need to form expectations about default rates and interest rates. The expectation about the effective return on loans $\mathrm{E}_{c,t}[r^L] = (1-\mathrm{E}_{c,t}[\rho^L])\tilde{r}^L_{c,t-1} - \mathrm{E}_{c,t}[\rho^L]$ is a function of the stochastic default rate ρ^L, which is exogenous in our model. For the sake of simplicity, we assume that cb-agents know the underlying stochastic process and can compute its moments, i.e. $\mathrm{E}_{c,t}[\rho^L] = \mu^{\rho^L}_{c,t}$ and $\sqrt{\mathrm{Var}_{c,t}(\rho^L)} = \sigma^{\rho^L}_{c,t}$.

In the context of our model, it seems reasonable to assume that the current overnight and long-term interest rates reflect all available information. Therefore, agents can expect the future rates to be the current rates, i.e. $\mathrm{E}_{c,t}[r^B] = r^B_{c,t}$ and $\mathrm{E}_{c,t}[r^I] = r^I_{c,t}$. The expected value of the average overnight interest paid $\bar{r}^I_{i,t}$ takes into account the possibility that a cb-agent's demand for overnight debt is not completely met by ib-agents, in which case the excess demand for overnight debt will be covered by the lender of last resort. The expected value of the average overnight interest rate amounts to:

$$\mathop{\mathrm{E}}_{c,t}[\bar{r}^I] = (1 - \mathrm{E}_{c,t}[a^{LLR}]) \mathop{\mathrm{E}}_{c,t}[r^I] + \mathrm{E}_{c,t}[a^{LLR}] \mathop{\mathrm{E}}_{c,t}[r^{LLR}], \tag{2.13}$$

with $a^{LLR}_{c,t} = I_{c,LLR,t}/I_{c,t}$ being the fraction of overnight debt borrowed from the central bank at time t. Taking into account that the necessity for central bank funding may be erratic rather than smooth, the expected value of a^{LLR} is modeled as an exponentially weighted moving average (EWMA) $\mathrm{E}_{c,t}[a^{LLR}] := \hat{\mathrm{E}}_{c,t}[a^{LLR}, \psi^I]$. We define the EWMA-operator as follows: $\hat{\mathrm{E}}_t[x, \psi] := (1 - \psi)\hat{\mathrm{E}}_{t-1}[x] + \psi x_t$, with ψ being a memory parameter that determines the weight of the latest observation of x.[16] With expectations of overnight funding costs, the expected marginal wholesale refinancing cost needed for the decision on whether to issue new loans or not (see Eq. (2.8)) amounts to

$$\mathop{\mathrm{E}}_{c,t}[r^{\Delta W}] = \begin{cases} a_{c,t}\,\mathrm{E}_{c,t}[r^B] + (1 - a_{c,t})\,\mathrm{E}_{c,t}[\bar{r}^I] & \text{if} \quad W_{c,t} > 0 \\ r^D_{c,t} & \text{if} \quad W_{c,t} = 0 \end{cases} \tag{2.14}$$

Each period maturing long-term debt needs to be refinanced. Cb-agents therefore worry about the expected volatility of long-term interest rates $\hat{\mathrm{Var}}_t(r^B, \psi^B)$. The EWMA-operator for the expected variance is defined as

[15] The trust component is motivated by relatively recent empirical evidence showing that the frequency of past transactions between two parties is a good indicator for current links in the interbank market (see e.g. Cocco et al., 2009; Finger and Lux, 2014; Craig et al., 2015).

[16] By using exponentially weighted moving averages (and variances), we can control how quickly past events become irrelevant to present decision making.

follows: $\hat{\text{Var}}_t(x,\psi) := \hat{\text{E}}_t\left[(x-\hat{\text{E}}_t[x,\psi])^2,\psi\right]$. Assuming, for the sake of simplicity, a constant interest rate r^{LLR} of the central bank's marginal lending facility and that $a^{LLR}_{c,t}$ and $r^I_{c,t}$ are independent, the expected variance of the average overnight interest rate amounts to

$$\begin{aligned}\hat{\text{Var}}_{c,t}(\bar{r}^I,\psi^I) &= \hat{\text{E}}_{c,t}\left[(\bar{r}^I-\hat{\text{E}}_{c,t}[\bar{r}^I,\psi^I])^2,\psi^I\right]\\ &= \hat{\text{E}}_{c,t}\left[(a^{LLR}-\hat{\text{E}}_{c,t}[a^{LLR},\psi^I])^2(r^{LLR}-r^I)^2,\psi^I\right]. \end{aligned} \tag{2.15}$$

2.5 Modeling Investment Banks

This section describes the properties and behavioral rules of ib-agents. Section 2.5.1 presents the peculiarities of the balance sheet of ib-agents. In contrast to cb-agents, ib-agents can flexibly adjust the size and structure of their balance sheet and do so by solving a complex portfolio optimization problem. The solution to this problem determines not only the composition of the assets of ib-agents, but also size of their balance sheet as well as the composition of their liabilities. Section 2.5.2 describes how ib-agents do this. After they have determined their asset allocations, ib-agents allocate the share of their portfolio that they want to invest in overnight debt across cb-agents. How ib-agents allocate funds on the overnight debt market is presented in Section 2.5.3. Finally, Section 2.5.4 describes how ib-agents calculate expected returns and covariances, which are the inputs to their portfolio optimization problem.

2.5.1 Balance Sheet

The balance sheet of ib-agent $i \in \{1,2,...,n^I\}$ at the end of period t has the following structure:

Assets		Liabilities	
Nb-securities,	$\sum_{s\in\mathcal{Q}^S_{\text{long}}} Q^S_{i,s,t}P^S_{s,t}$	Repos,	$\sum_{s=1}^{n^S} R_{i,s,t}$
Overnight Interbank Loans,	$\sum_{c=1}^{n^C} I_{c,i,t}$	Nb-securities (short),	$\sum_{s\in\mathcal{Q}^S_{\text{short}}} \lvert Q^S_{i,s,t}\rvert P^S_{s,t}$
Bank Bonds,	$\sum_{c=1}^{n^C} Q^B_{i,c,t}P^B_{c,t}$	Investor Deposits	$D_{i,t}$
Margin Account,	$\sum_{s=1}^{n^S} M_{i,s,t}$	Equity,	$E_{i,t}$
Cash,	$C_{i,t}$		

with non-bank securities (nb-securities) consisting of n^S different debt instruments (e.g. government and corporate bonds) that are not issued by banks. We define $Q^S_{i,s,t} \in \mathbb{R}$ as the quantity of nb-security s held by agent i at time t and $P^S_{s,t}$ as its current price. All nb-securities can be used as collateral in a repo transaction and borrowed for the purpose of short selling. When the asset is borrowed and sold short, the quantity of an nb-security is negative and qualifies as debt. Formally, $\mathcal{Q}^S_{\text{short}} := \{s|Q^S_{i,s,t} < 0\}$ defines the set of nb-securities that are shorted by agent i at time t and $\mathcal{Q}^S_{\text{long}} := \{s|Q^S_{i,s,t} \geq 0\}$ defines the set of nb-securities to which that agent has a positive exposure at time t. In accordance with short selling regulation and business practice, ib-agents are required to hold the cash they receive from shorting an asset (plus an extra margin to protect the security lender) in a margin account. Ib-agent i holds $Q^B_{i,c,t} \geq 0$ bank bonds issued by cb-agent c. $P^B_{c,t}$ denotes the current price at which the bonds are traded. Investor deposits $D_{i,t}$ are uninsured and in contrast to household deposits $D_{c,t}$ on cb-agents' balance sheets, they fluctuate endogenously (see Section 2.6.3).

The balance sheet of ib-agents evolves with their portfolio decisions described in the next section. We assume that all principal and interest rate payments on assets are collected at the beginning of a period before portfolios are restructured. Analogous to the modeling of commercial banks, ib-agents have an equity target E^*_i and cannot issue new equity. Therefore, $E_{i,t} = \min\{E^*_i, E_{i,t-1} + \Pi_{i,t}\}$. Profits $\Pi_{i,t} = \Pi^I_{i,t} + \Pi^B_{i,t} + \Pi^S_{i,t} - \Pi^F_{i,t}$ are generated through investments in overnight interbank loans, bank bonds and nb-securities; they are reduced by the funding costs:

$$\Pi^I_{i,t} = \sum_{c \in \mathcal{S}} I_{c,i,t-1} r^I_{i,c,t-1} - \sum_{c \in \mathcal{S}^{-1}} I_{c,i,t-1} \tag{2.16}$$

$$\begin{aligned}\Pi^B_{i,t} =& \sum_{c \in \mathcal{S}} Q^B_{i,c,t-1} \left(\frac{B_{c,t-1}}{Q^B_{c,t-1}} \bar{r}^B_{c,t-1} + (1 - m_B)(\frac{B_{c,t-1}}{Q^B_{c,t-1}} - P^B_{c,t-1}) + m_B(P^B_{c,t} - P^B_{c,t-1}) \right) \\ & - \sum_{c \in \mathcal{S}^{-1}} Q^B_{i,c,t-1} P^B_{c,t-1}\end{aligned} \tag{2.17}$$

$$\Pi^S_{i,t} = \sum_{s=1}^{n^S} Q^S_{i,s,t-1} \left(\frac{V^S_{s,t-1}}{Q^S_s} \bar{r}^S_{s,t-1} + (1 - m_S)(\frac{V^S_{s,t-1}}{Q^S_s} - P^S_{s,t-1}) + m_S(P^S_{s,t} - P^S_{s,t-1}) \right) \tag{2.18}$$

$$\Pi^F_{i,t} = r^D_{i,t-1} D_{i,t-1} + r^R_{i,t-1} R_{i,s,t-1} + r^M_{i,t-1} M_{i,s,t-1} \tag{2.19}$$

We define $\mathcal{S} := \{c|E_{c,t} > 0\}$ and $\mathcal{S}^{-1} := \{c|E_{c,t} \leq 0\}$ as the set of solvent and insolvent cb-agents, respectively. For the sake of simplicity, we assume that the loss given a cb-agent's default is 100%. Each ib-agent may charge a different interest rate $r^I_{i,c,t}$ on overnight loans to cb-agents, while there is just one current interest rate $\bar{r}^B_{c,t}$ on the tradable portfolio of a cb-agent's bank bonds. Beside interest payments on bank bonds, ib-agents receive a principal payment on maturing bonds and register a profit or loss from price changes on outstanding bonds. The ratio $B_{c,t}/Q^B_{c,t}$ specifies the nominal value of a bank bond, which is the basis for interest and principal payments. Similar to bank bonds, there are also three profit-components to nb-securities: interest payments, principal payments and price changes. We define V^S and Q^S as the nominal value and constant quantity of outstanding nb-securities, respectively. While $1 - m_S$ defines the constant repayment rate of nb-securities, we assume, for the sake of simplicity, that all maturing shares are immediately reissued each period. Funding costs depend on the exogenous interest rates for repo transactions ($r^R_{i,t}$), short selling transactions ($r^M_{i,t}$) and investor deposits ($r^D_{i,t}$).

2.5.2 Asset And Liability Management

Ib-agents decide on the desired composition of their balance sheet each period by computing a weights-vector $\mathbf{a}_{i,t} = (\mathbf{a}^S_{i,t}, \mathbf{a}^B_{i,t}, \mathbf{a}^M_{i,t}, \mathbf{a}^R_{i,t}, a^D_{i,t}, a^I_{i,t}, a^C_{i,t})'$ which defines the ratios of balance sheet positions to equity $E_{i,t}$. The vector $\mathbf{a}_{i,t}$ contains four sub-vectors which comprise the individual weights of nb-securities $\mathbf{a}^S_{i,t} = (a^S_{i,1,t}, ..., a^S_{i,n^S,t})'$, bank bonds $\mathbf{a}^B_{i,t} = (a^B_{i,1,t}, ..., a^B_{i,n^C,t})'$, margin account deposits $\mathbf{a}^M_{i,t} = (a^M_{i,1,t}, ..., a^M_{i,n^S,t})'$, repo liabilities $\mathbf{a}^R_{i,t} = (a^R_{i,1,t}, ..., a^R_{i,n^S,t})'$ as well as weights for investor deposits $a^D_{i,t}$, a composite overnight interbank asset $a^I_{i,t}$ and cash $a^C_{i,t}$.[17] The specific weights are derived from the following mean-variance optimization problem (the solution algorithm is described in Appendix 2.10.5):

$$\mathbf{a}^*_{i,t} = \arg\max_{\mathbf{a}} \mathbf{a}' \mathrm{E}_{i,t}[\mathbf{r}] - 0.5\lambda_i \mathbf{a}' \mathbf{\Sigma}_{i,t} \mathbf{a} \qquad \text{s.t.} \tag{2.20}$$

$$a^R_{i,s,t} = \begin{cases} -(1 - h^R_{s,t}) a^S_{i,s,t} & \text{if } a^S_{i,s,t} \geq 0 \text{ and } h^R_{s,t} \leq h^D_{i,t} \\ 0 & \text{else} \end{cases} \tag{2.21}$$

$$a^M_{i,s,t} = \begin{cases} -(1 + k_{s,t}) a^S_{i,s,t} & \text{if } a^S_{i,s,t} < 0 \\ 0 & \text{else} \end{cases} \tag{2.22}$$

$$a^D_{i,t} = -(1 - h^D_{i,t})(a^I_{i,t} + \sum_{c=1}^{n^C} a^B_{i,c,t} + \sum_{s \in \mathcal{D}} a^S_{i,s,t}) \tag{2.23}$$

$$\{a^I_{i,t}, a^B_{i,c,t}, a^C_{i,t}\} \geq 0 \quad \text{and} \quad \mathbf{a}'\mathbf{1} = 1 \tag{2.24}$$

with $\mathrm{E}_{i,t}[\mathbf{r}] = (\mathrm{E}_{i,t}[\mathbf{r}^S], \mathrm{E}_{i,t}[\mathbf{r}^B], \mathbf{r}^M_{i,t}, \mathbf{r}^R_{i,t}, r^D_{i,t}, \mathrm{E}_{i,t}[r^I], r^C_{i,t})'$ being a vector containing the expected returns of balance sheet positions of investment bank i, λ_i being its risk aversion parameter, $\mathbf{\Sigma}_{i,t}$ being agent i's estimate of the $N \times N$ variance-covariance matrix of asset returns ($N = 3n^S + n^C + 3$) and $\mathbf{1}$ denoting a $N \times 1$ vector of ones. The variables $h^R_{s,t}$ and $k_{s,t}$, which are derived in Section 2.6.2, are the haircut and margin requirement on repo and short-selling transactions, respectively. Section 2.6.3 explains how the funding provided by institutional investors in the form of deposits translates into the haircut $h^D_{i,t}$.[18] The constraints in Eqs. (2.21) and (2.22) respectively specify the relation between nb-securities and repo funding and between margin accounts and investor deposits. We assume that ib-agents, which can choose to fund nb-securities either through repos or investor deposits, choose the debt form with the lower haircut. The weight for investor deposits, defined in Eq. (2.23), thus needs to consider long positions in nb-securities for $s \in \mathcal{D}$ with $\mathcal{D} := \{s | (a^S_{i,s,t} \geq 0) \wedge (h^R_{s,t} > h^D_{i,t})\}$. Note that when ib-agent i purchases an nb-security, it automatically engages in a repo transaction or debt relationship with an investor and receives $1 - h^R_{s,t}$ or $1 - h^D_{i,t}$ times the current value of asset s as a cash-loan from a central coun-

[17] We choose to include a composite overnight asset instead of individual interbank loans in the portfolio optimization in order to reduce computational complexity. The next section describes overnight interbank funds are allocated across individual counterparties.

[18] In general, the haircut $h^R_{s,t}$ of a repo transaction is defined as the percentage difference between the value of one unit of collateral (i.e. the price of nb-security s) and the loan received in exchange for the collateral. This definition implies that the higher the haircut, the more equity capital is needed to finance the purchase of nb-security s. In effect, the haircut puts a limit to an agent's leverage: Because h^R is the fraction of total assets (TA) that has to be financed with equity capital, the relation $\mathrm{TA}^{max} * h^R = E_t$ defines the maximum balance sheet size (TA^{max}) that can be achieved through repo-financing. From the definition of leverage (debt divided by equity) the maximum leverage can be computed as $\mathrm{lev}^{max} = (\mathrm{TA}^{max} - E)/E = 1/h^R - 1$. The concept of the haircut is therefore useful beyond the context of a repo transaction. It can be used to introduce capital requirements (both, in the form of risk weights and a leverage ratio) into the portfolio maximization problem of ib-agents.

terparty or institutional investors.[19] In a short selling transaction, the central counterparty will require the agent to deposit $1 + k_{s,t}$ times the current value of asset s in a margin account. Finally, the constraints in Eq. (2.24) make sure that interbank assets, bonds and cash cannot be shorted and that the budget constraint is met.

From the vector of optimal weights $\mathbf{a}^*_{i,t}$ we can derive the balance sheet positions of nb-securities and their corresponding margin and repo accounts. The aspired quantity $Q^S_{i,s,t}$ for the asset s amounts to $Q^S_{i,s,t} = \frac{a^S_{i,s,t} E_{i,t}}{P^S_{s,t}}$, while the quantity traded is $\Delta Q^S_{i,s,t} = Q^S_{i,s,t} - m_S Q^S_{i,s,t-1}$. Repos, margin account positions and investor deposits are given by $R_{i,s,t} = a^R_{i,s,t} E_{i,t}$, $M_{i,s,t} = a^M_{i,s,t} E_{i,t}$ and $D_{i,t} = a^D_{i,t} E_{i,t}$, respectively. Cash holdings $C_{i,t}$ are determined by two factors: They may result from the portfolio maximization problem and they may accumulate due to failed transactions in the overnight interbank market and bond market. Therefore

$$C_{i,t} = a^C_{i,t} E_{i,t} + a^I_{i,t} E_{i,t} + \sum_{c=1}^{n^C} a^B_{i,c,t} E_{i,t} - \sum_{c=1}^{n^C} (I_{c,i,t} + Q^B_{i,c,t} P^B_{c,t}). \qquad (2.25)$$

Some transactions inevitably fail when the pricing mechanisms for overnight loans (see next section) and bank bonds (see Section 2.6.5) fall short of achieving complete market clearing.

2.5.3 Overnight Loans And Bank Bonds

The portfolio weight $a^B_{i,c,t}$ implies an investment target of $B_{i,c,t} = a^B_{i,c,t} E_{i,t}$ in bonds issued by cb-agent c. In case of excess demand, i.e. $\sum_{i=1}^{n^I} B_{i,c,t} > B_{c,t}$, the available bonds are allocated to ib-agents in proportion to their relative demands. The quantity of bonds on the balance sheet of agent i at time t is thus defined as

$$Q^B_{i,c,t} = \begin{cases} B_{i,c,t}/P^B_{c,t} & \text{if } \sum_{i=1}^{n^I} B_{i,c,t} \leq B_{c,t} \\ \frac{B_{i,c,t}}{P^B_{c,t}} \frac{B_{c,t}}{\sum_{i=1}^{n^I} B_{i,c,t}} & \text{else} \end{cases}, \qquad (2.26)$$

implying a trading quantity of $\Delta Q^B_{i,c,t} = Q^B_{i,c,t} - m_B Q^B_{i,c,t-1}$.

The allocation of overnight interbank loans to individual cb-agents is not directly determined in the portfolio optimization. In order to allocate $a^I_{i,t} E_{i,t}$ of overnight interbank loans, ib-agents first evaluate cb-agents. The evaluation is a function of three factors $U^I_{i,c,t}(v_{c,i,t}, \mathrm{E}_{i,t}[r^I_c], \mathrm{Var}_{i,t}(r^I_c))$, with $v_{c,i,t}$ defining the trust between the counterparties (see Section 2.4.4), $\mathrm{E}_{i,t}[r^I_c]$ being the expected return and $\mathrm{Var}_{i,t}(r^I_c)$ the expected variance of returns of an overnight interbank loan to agent c. The ratio used to allocate overnight funds to individual cb-agents is a function of the evaluation function, i.e. $a^I_{i,c,t}(U^I_{i,c,t})$. The details of both the evaluation and allocation functions are given in Appendix 2.10.6. By multiplying the allocation ratio $a^I_{i,c,t}$ with the composite interbank asset weight, we obtain the supply of overnight interbank loans, i.e. $I_{i,c,t} = a^I_{i,t} a^I_{i,c,t} E_{i,t}$.

[19] These automatic debt relationship may cause the liabilities side of balance sheets to be larger than necessary. However, excess funding will be held in cash and will therefore not add any risk to agents' balance sheets.

The discrepancy between demand and supply for overnight interbank loans $\Delta I_{i,c,t}$ is important for the pricing of the loans. We assume that a cb-agent's excess demand for overnight loans, which will be met by the central bank, will be distributed according to the cb-agent's evaluation of the ib-agent's offer $U^C_{c,i,t}$, i.e.

$$\Delta I_{i,c,t} = \begin{cases} I_{c,i,t} - I_{i,c,t} & \text{if } I_{i,c,t} \geq I_{c,i,t} \\ \frac{I_{c,LLR,t} U^C_{c,i,t}}{\sum_{i=1}^{n^I} U^C_{c,i,t}} & \text{if } I_{i,c,t} < I_{c,i,t}. \end{cases} \tag{2.27}$$

Ib-agents minimize the discrepancy between supply and demand, $\Delta I_{i,c,t}$, by negotiating with cb-agents over the volume and interest rate of overnight interbank debt. We model these negotiations via an iterative algorithm that in essence performs the task of a Walrasian auctioneer: The auctioneer posts an interest rate, checks loan supply and demand at the posted rate, reacts to the discrepancy between supply and demand by adjusting the interest via a logarithmic impact function and repeats the procedure. For the sake of confining computational complexity, the auction is terminated after Φ_t iterations, after which the actual transactions will take place. The logarithmic impact function used to adjust interest rates has the following form:

$$\log(r^I_{i,c,t+\frac{\phi}{\Phi_t}}) = \log(r^I_{i,c,t+\frac{\phi-1}{\Phi_t}}) + g^I \frac{\Delta I_{i,c,t+\frac{\phi-1}{\Phi_t}}}{|I_{c,i,t+\frac{\phi-1}{\Phi_t}}| + |I_{i,c,t+\frac{\phi-1}{\Phi_t}}|}, \tag{2.28}$$

with $\phi \in \{1, 2, ..., \Phi_t\}$ being the iteration count. The parameter $g^I > 0$ determines the intensity with which interest rate adjustments take place in dependence of the differences in demand and supply on the interbank market. By dividing $\Delta I_{i,c,t}$ by the sum of absolute values of loan demand and loan supply, we bound changes to the interest rate within one iteration. The maximum percentage change of the interest rate in either direction is approximately the value of the intensity parameter g^I.

2.5.4 Expectation Formation

Ib-agents' expectations about the returns and variances of nb-securities, bank bonds and overnight interbank loans are key inputs to their portfolio optimization problems. The expected return of nb-security s is deduced by forecasting its default probability Ω^S_s and price P^S_s. Taking into account the exogenously given maturity m_S and nominal interest rate $\bar{r}^S_{s,t}$, the expected return of asset s is computed as follows:

$$\underset{i,t}{\mathrm{E}}[r^S_s] = (1 - \underset{i,t}{\mathrm{E}}[\Omega^S_s]) \left(\frac{V^S_s}{P^S_{s,t} Q^S_s} (\bar{r}^S_{s,t} + 1 - m_S) + \frac{m_S \,\mathrm{E}_{i,t}[P^S_s]}{P^S_{s,t}} - 1 \right) - \underset{i,t}{\mathrm{E}}[\Omega^S_s], \tag{2.29}$$

with $V^S_{s,t}$ being the nominal value of the nb-security and Q^S_s the number of outstanding shares. For the sake of simplicity, we assume that ib-agents believe that prices adjust immediately so that they incorporate all available information (i.e. $\mathrm{E}_{i,t}[P^S_s] = P^S_{s,t}$) and that the loss in case of a default is expected to be 100%. An ib-agent's assessment of the true default probability $\Omega^S_{s,t}$ is updated by evaluating fundamental news shocks $\Delta\Omega^S_{s,t} = \log(\Omega^S_{s,t}) - \log(\Omega^S_{s,t-1})$ and by identifying and correcting past valuation errors:

$$\mathop{\mathrm{E}}_{i,t}\left[\log(\Omega_s^S)\right] = \underbrace{\mathop{\mathrm{E}}_{i,t-1}\left[\log(\Omega_s^S)\right]}_{\text{past valuation}} + \underbrace{(\Delta\Omega_{s,t}^S + \epsilon_{i,s,t}^S)}_{\text{evaluation of news}} + \underbrace{\theta^S\left(\log(\Omega_{s,t}^S) - \mathop{\mathrm{E}}_{i,t-1}\left[\log(\Omega_s^S)\right]\right)}_{\text{past error correction}} \tag{2.30}$$

The stochastic error term $\epsilon_{i,s,t}^S$ and the slow correction of past errors (i.e. $\theta^S < 1$) cause forecasts of the true default probability to differ. Disagreement about the true value of an asset is the necessary condition for the emergence of a functioning asset market in our model.

In the calculation of the variance of nb-securities, ib-agents consider the associated default risk and a measure of their past forecasting errors:

$$\begin{aligned}\mathop{\mathrm{Var}}_{i,t}(r_s^S) = \left(1 - \mathop{\mathrm{E}}_{i,t}[\Omega_s^S]\right)\hat{\mathrm{E}}_{i,t}&\left[\left(\frac{V_{s,t}^S}{P_{s,t}^S Q_{s,t}^S}(\bar{r}_{c,t-1}^S + 1 - m_S) + \frac{m_S P_{s,t}^S}{P_{s,t-1}^S} - 1 - \mathop{\mathrm{E}}_{i,t-1}[r_s^S]\right)^2, \psi^S\right] \\ &+ \mathop{\mathrm{E}}_{i,t}[\Omega_s^S]\left(-1 - \mathop{\mathrm{E}}_{i,t}[r_s^S]\right)^2\end{aligned} \tag{2.31}$$

The higher the historical discrepancy between agent i's return expectation and the realized return, the higher will be the agent's perception of risk (variance). Estimates of covariances, on the other hand, account for historical co-movements in assets and are important for the purpose of building a diversified portfolio. We assume that all agents have the same estimates of the covariance $\hat{\mathrm{Cov}}_t(r_{s1}^S, r_{s2}^S, \psi^S)$ between two assets, which are computed as an exponentially weighted moving average of daily returns.

The expected returns and variances of overnight interbank loans and bonds depend on the expected default probabilities of the corresponding cb-agents. Taking into account the exogenous loan default process $\rho_{c,t}^L$, we can approximate the default probability of cb-agents as $\Omega_{c,t}^C \approx \Pr\{\rho_{c,t}^L L_{c,t} \geq E_{c,t}\}$. Since data on equity $E_{c,t}$, loan volume $L_{c,t}$ and the loan default rate distribution of cb-agents are not readily available to investment banks on a daily basis, we model expectations of the default probability analogous to that of nb-securities:

$$\mathop{\mathrm{E}}_{i,t}[\log(\Omega_c^C)] = \mathop{\mathrm{E}}_{i,t-1}[\log(\Omega_c^C)] + \left(\Delta\Omega_{c,t}^C + \epsilon_{i,c,t}^\Omega\right) + \theta^\Omega\left(\log(\Omega_{c,t}^C) - \mathop{\mathrm{E}}_{i,t-1}[\log(\Omega_c^C)]\right), \tag{2.32}$$

with $\Delta\Omega_{c,t}^C = \log(\Omega_{c,t}^C) - \log(\Omega_{c,t-1}^C)$ being the news shock, $\epsilon_{i,c,t}^\Omega$ denoting the stochastic valuation error and θ^Ω being the speed with which past valuation errors are corrected.

The derivation of expected return and variance of overnight interbank loans and bank bonds is similar to that of nb-securities:

$$\mathop{\mathrm{E}}_{i,t}[r_c^I] = (1 - \mathop{\mathrm{E}}_{i,t}[\Omega_c^C])r_{i,c,t}^I - \mathop{\mathrm{E}}_{i,t}[\Omega_c^C] \quad \text{and} \tag{2.33}$$

$$\mathop{\mathrm{E}}_{i,t}[r_c^B] = (1 - \mathop{\mathrm{E}}_{i,t}[\Omega_c^C])\left(\frac{B_{c,t}}{P_{c,t}^B Q_{c,t}^B}(\bar{r}_{c,t}^B + 1 - m_B) + \frac{m_B\,\mathrm{E}_{i,t}[P_c^B]}{P_{c,t}^B} - 1\right) - \mathop{\mathrm{E}}_{i,t}[\Omega_c^C]. \tag{2.34}$$

Note that because overnight interbank loans are not traded, they lack a price. As with nb-securities, we assume that ib-agents expect tomorrow's bond price to equal the current price, i.e. $\mathrm{E}_{i,t}[P_c^B] = P_{c,t}^B$. The variance components of overnight interbank loans and bonds are defined as follows:

$$\underset{i,t}{\mathrm{Var}}(r_c^I) = \left(1 - \underset{i,t}{\mathrm{E}}[\Omega_c^C]\right)\left(r_{i,c,t}^I - \underset{i,t}{\mathrm{E}}[r_c^I]\right)^2 + \underset{i,t}{\mathrm{E}}[\Omega_c^C]\left(-1 - \underset{i,t}{\mathrm{E}}[r_c^I]\right)^2 \tag{2.35}$$

$$\underset{i,t}{\mathrm{Var}}(r_c^B) = \left(1 - \underset{i,t}{\mathrm{E}}[\Omega_c^C]\right)\hat{\mathrm{E}}_{i,t}\left[\left(\frac{B_{c,t}}{P_{c,t}^B Q_{c,t}^B}(\bar{r}_{c,t-1}^B + 1 - m_B) + \frac{m_B P_{c,t}^B}{P_{c,t-1}^B} - 1 - \underset{i,t-1}{\mathrm{E}}[r_c^B]\right)^2, \psi^B\right]$$
$$+ \underset{i,t}{\mathrm{E}}[\Omega_c^C]\left(-1 - \underset{i,t}{\mathrm{E}}[r_c^B]\right)^2 \tag{2.36}$$

With the individual expected return and variance components for overnight interbank loans, the return and variance for the composite overnight interbank asset are given by $\mathrm{E}_{i,t}[r^I] = \sum_{c=1}^{n^C} a_{i,c,t}^I \, \mathrm{E}_{i,t}[r_c^I]$ and $\mathrm{Var}_{i,t}(r^I) = \sum_{c=1}^{n^C} (a_{i,c,t}^I)^2 \, \mathrm{Var}_{i,t}(r_c^I)$, respectively. The covariance $\hat{\mathrm{Cov}}_{i,t}(r_c^B, r^I, \psi^S)$ between the composite overnight interbank asset and bonds, between nb-securities and the composite asset $\hat{\mathrm{Cov}}_{i,t}(r^I, r_s^S, \psi^S)$ as well as between nb-securities and bonds $\hat{\mathrm{Cov}}_{i,t}(r_c^B, r_s^S, \psi^S)$ are computed as exponentially weighted moving averages of observed returns.

2.6 Modeling Exogenous Agents

Several exogenous agents help to close the model. These are a central counterparty for repo transactions and short selling, an institutional investor, which provides deposits for ib-agents, a market maker, which sets the prices and interest rates as well as a lender of last resort. Furthermore, we incorporate an agent labeled "rest-of-world", which trades on the same asset markets as investment banks do.

2.6.1 Rest-of-world Agent

The rest-of-world agent (row-agent) is included into the setup in order to keep the simulated financial system from becoming artificially fragile and in order to introduce the concept of asset liquidity. In reality, when the usual buyers of specific assets (ib-agents in our context) are constrained, it falls to outside investors to absorb the excess supply of those assets. The row-agent represents these outside investors, which could include e.g. pension funds, insurance companies, unregulated financial institutions or individual investors. Because the row-agent by assumption is not specialized in assessing and trading the assets in question, we assume that it demands a higher return. This implies that the price of assets must drop below the mean valuation of ib-agents before the row-agent becomes active. The more reluctant the row-agent is to buying an asset of a given risk/return profile, the less liquid that asset will be.[20]

The demand of the row-agent for nb-securities and bank bonds is derived from a portfolio optimization problem similar to that of ib-agents:

$$\mathbf{a}_{row,t}^* = \arg\max_{\mathbf{a}} \mathbf{a}'\mathrm{E}_{row,t}[\mathbf{r}] - 0.5\lambda_{row}\mathbf{a}'\mathbf{\Sigma}_{row,t}\mathbf{a} \qquad \text{s.t.} \tag{2.37}$$

[20] Our concept of the row-agent strongly relates to the seminal discussion on asset liquidity and debt capacity in Shleifer and Vishny (1992). It is also related to the empirical literature on price impacts in financial markets. See for example Coval and Stafford (2007) or Jotikasthira et al. (2012) for estimates of price impact in stock markets and Ellul et al. (2011) or Feldhuetter (2012) for estimates in bond markets.

$$\{a^S_{row,s,t}, a^B_{row,c,t}, a^C_{row,t}\} \geq 0 \quad \text{and} \quad \mathbf{a}'\mathbf{1} = 1, \tag{2.38}$$

with $\mathbf{a}_{row,t} = (a^S_{row,1,t}, ..., a^S_{row,n^S,t}, a^B_{row,1,t}, ..., a^B_{row,n^C,t}, a^C_{row,t})'$ being a weights vector defining the desired value of individual nb-securities and bank bonds as a multiple of equity $E_{row,t}$. The expected returns contained in the vector $\mathrm{E}_{row,t}[\mathbf{r}]$ and the estimated variances and covariances contained in the matrix $\mathbf{\Sigma}_{row,t}$ are computed analogously to those of ib-agents as defined in Section 2.5.4. Expectations differ in two regards: first, because the row-agent represents a group of investors, its expectations of the default probabilities $\Omega^S_{s,t}$ and $\Omega^C_{c,t}$ are set to their respective true value. Second, we assume that the agent is willing to hold an asset to maturity and therefore ignores the price volatility of assets, i.e. price changes disappear from the variance estimates. In this context, it seems reasonable to assume that investors lacking the experience of trading a specific asset will not hold that asset in their trading book, which might be subject to mark-to-market accounting rules. They will rather identify the long-term benefit from holding an asset that is undervalued to maturity. For the sake of simplicity, we assume that the row-agent cannot incur debt, which is implied by the constraint in Eq. (2.38). To ensure that enough funds are available to eventually absorb assets in a fire sale spiral, we model equity of the row-agent as a function of the difference between ib-agents' current equity and equity target E^*:

$$E_{row,t} = \max\left\{ x^{row}\left(\sum_{i=1}^{n^I} E^*_i - E_{i,t}\right)^2, E^{\min}_{row}\right\}, \tag{2.39}$$

with $E^{\min}_{row}$ denoting a fixed minimum equity of the row-agent and the parameter $x^{row} > 0$ defining the factor with which row-equity is increased when ib-agents make losses.[21] The demand $\Delta Q^S_{row,s,t}$ for nb-security s is $\Delta Q^S_{row,s,t} = \frac{a^S_{row,s,t} E_{row,t}}{P^S_{s,t}} - m^S Q^S_{row,s,t-1}$, with $Q^S_{row,s,t-1}$ denoting the quantity held by the row-agent in the last period. The demand for bank bonds is calculated in the same manner.

The vector λ_{row} contains a risk aversion parameter for each nb-security and bank bond. The parameters are set orders of magnitude larger than the risk aversion of ib-agents. This ensures that the row-agent does not distort prices in normal times. By assigning an individual risk aversion to each asset in the portfolio of the row-agent, we can make some assets more liquid than others. The higher the specific risk aversion parameter of an asset is relative to other assets, the larger must be the price drop before the row-agent absorbs that asset. Fire sale dynamics of illiquid (higher risk aversion) assets therefore become more pronounced than for liquid (lower risk aversion) assets.

2.6.2 Central Counterparty

We assume, for the sake of simplicity, that the central counterparty is always willing to engage in short selling and repo transactions with ib-agents. The

[21] The function for $E_{row,t}$ is rather ad hoc. It is motivated by the notion that when asset prices fall below the respective values deemed fair by constrained ib-agents, they will increasingly attract outside investors. A greater number of outside investors will have more equity and hence capacity to absorb assets.

central counterparty thereby manages its risk by setting the haircut and margin requirement for the corresponding asset. The amount of cash the investor is willing to lend in a repo transaction depends on the current price of the collateral $P_{s,t}^S$ and the haircut $h_{s,t}$. Specifically, the central counterparty chooses the haircut so that the probability of the collateral being worth less than the loan provided does not exceed x^R, i.e. $\Pr\{P_{s,t+1}^S \leq P_{s,t}^S(1-h_{s,t})\} = \Pr\{r_{s,t}^S \leq -h_{s,t}\} = x^R$. With F_s^{-1} denoting the quantile function of the return of asset s in the next period, the haircut is computed as follows:

$$h_{s,t} = -F_s^{-1}(x^R). \tag{2.40}$$

The margin requirement $k_{s,t}$ can be computed analogously. Specifically, $k_{s,t} = F_s^{-1}(1-x^R)$, which is equal to $h_{s,t}$ if the probability density function of the return of the corresponding asset is symmetric around zero. As a compensation for its risk, the central counterparty will demand a small fee of r_t^R and r_t^M for repo and short selling transactions, respectively.

2.6.3 Investor Deposits

Unlike customer deposits, investor deposits are uninsured and therefore potentially very volatile. The volume of funds investors are willing to lend depends on the profitability of the debtor agent and the speed at which the investor can withdraw funds. We assume that deposits cannot be withdrawn at once, but at a constant rate of $1-m_D$, where m_D is the maturity parameter. Without specifying the return on deposits, we assume that it is proportional to the debtor agent's return on assets $\pi_{i,t}$. Since investors only lose money if the debtor agent defaults, it seems sensible that investors consider a default scenario when deciding on how much they want to lend to investment banks. Specifically, investors consider a predefined stress scenario of a daily negative return on assets $\rho_{i,t}^D$, which eventually leads to the default of the debtor agent.[22] Under such a stress scenario the investor would try to withdraw its funds as quickly as possible. Taking this into account, the initial investment $D_{i,t}^*$ is chosen in such a way that the funds D_i^{risk} not withdrawn at the time of bankruptcy (i.e. the loss for the investor) are smaller than a specified fraction $\alpha_D = D_i^{\text{risk}}/D_{i,t}^*$ of the initial investment. The resulting initial volume of deposits is given by (the derivation of $D_{i,t}^*$ is given in Appendix 2.10.7)

$$D_{i,t}^* = -\frac{(1+\rho_{i,t}^D)(1-\frac{m_D}{1+\rho_{i,t}^D})}{\rho_{i,t}^D\left(1-\left(\frac{m_D}{1+\rho_{i,t}^D}\right)^{T^{\text{def}}}\right)} E_{i,t}, \tag{2.41}$$

where T^{def} marks the period in which fraction of initial deposits not yet withdrawn reaches α^D. Under the setting described above, $D_{i,t}^*$ can be used to calculate the maximum leverage $\text{lev}_{i,t}^{max} = D_{i,t}^*/E_{i,t}$ of ib-agent i at time t. Any bound on leverage can be translated into a haircut parameter. With $\text{lev}_{i,t}^{max} = 1/h_{i,t}^D - 1$ we can derive $h_{i,t}^{D^*} = E_{i,t}/(E_{i,t}+D_{i,t}^*)$. Since investors

[22] A stress scenario could e.g. be defined as a daily return on assets which is one standard deviation to the left of the expected return on assets, with the expected value and variance or the return on assets being historical estimates ($\rho_{i,t}^D = \hat{\mathrm{E}}_t[\pi_i, \psi^D] - \sqrt{\hat{\mathrm{Var}}_t(\pi_i, \psi^D)}$).

cannot withdraw funds faster than they mature, the corresponding haircut has an upper bound, i.e. $h_{i,t}^{D} \leq E_{i,t-1}/(E_{i,t-1} + m_D D_{i,t-1})$. On the other hand, we assume that ib-agents are able to buy back debt, i.e. reduce investor deposits regardless of their maturity.

2.6.4 Lender Of Last Resort

The central bank acts as a lender of last resort by providing a marginal lending facility (discount window) to cb-agents. We assume that agents consider the central bank as a potential creditor in the interbank market.[23] It is ranked along with other creditors according to the same two factors as ib-agents (see Section 2.4.4). Borrowing from the central bank comes at a price. The marginal lending rate r_t^{LLR} is typically higher than interbank interest rates, which implies that $u_{c,LLR,t} \ll 1$. Furthermore, we assume that cb-agents fear that making use of the marginal lending facility might tarnish their reputation.[24] To account for this the trust factor is set to its lower bound.

2.6.5 Market Maker

Market prices for nb-securities and bonds in our model evolve endogenously according to demand and supply. Since the portfolio selection problem of ib-agents requires the agents' knowledge of the prices at which they can trade, we choose to price assets via an exogenous market maker. We assume that the market maker lacks information about the fundamentals of nb-securities and bonds. In order to limit its exposure to the risky assets, the market maker tries to learn the prices at which demand and supply for the respective assets are balanced. Since in the context of our model all trading occurs simultaneously, we choose the incomplete Walrasian auction introduced in Section 2.5.3 as the pricing mechanism.

In order to find the appropriate price of an nb-security, the market maker has to determine the market interest rate first. As in Eq. (2.28) the interest rate results from Φ_t iterations of a logarithmic impact function, which depends on the excess demand (normalized by the trading volume) of the market maker, the ib-agents and the row-agent:

$$\log(r^S_{s,t+\frac{\phi}{\Phi_t}}) = \log(r^S_{s,t+\frac{\phi-1}{\Phi_t}}) + g^{MMS} \left(\frac{\sum_{A=1}^{N^S} \mathbf{\Delta Q^S_{s,t+\frac{\phi-1}{\Phi_t},\mathrm{A}}}}{\sum_{A=1}^{N^S} |\mathbf{\Delta Q^S_{s,t+\frac{\phi-1}{\Phi_t},\mathrm{A}}}|} \right) \tag{2.42}$$

with $\phi \in \{1, 2, ..., \Phi_t\}$ being the iteration count, $g^{MMS} > 0$ being the intensity of interest rate adjustments and $\mathbf{\Delta Q^S}_{s,t+\frac{\phi-1}{\Phi_t}} = (-Q^{MMS}_{s,t}, \Delta Q^S_{1,s,t+\frac{\phi-1}{\Phi_t}}, ..., \Delta Q^S_{n^I,s,t+\frac{\phi-1}{\Phi_t}}, \Delta Q^S_{row,s,t+\frac{\phi-1}{\Phi_t}})'$ being a vector of length $N^S = 2 + n^I$ containing the quantities traded by the market maker agent, the ib-agents and the row-agent in the ϕ's iteration of period t. The quantity $Q^{MMS}_{s,t} = m_S Q^{MMS}_{s,t-1} + (1 - m_S) Q^S_s - \sum_{i=1}^{n^I} \Delta Q^S_{i,s,t} - \Delta Q^S_{row,s,t}$ denotes

[23] In practice, making use of the marginal lending facility requires a bank to post collateral in exchange for central bank money. However, non-marketable assets (including bank loans) are also eligible as collateral if they are rated above a certain threshold.

[24] This is consistent with the observation that even after the default of Lehman Brothers, only poorly performing US banks accessed the discount window (see Afonso et al., 2011).

the market maker's inventory. Note that the inventory of the market maker is increased by the maturing nb-securities ($(1-m_S)Q_s^S$) each period. This implies that the total number of shares of nb-security s remains constant throughout the simulation. The market price of nb-securities can be calculated by employing a present value approach of the flow of interest payments and repayments discounted at the market interest rate $r_{s,t}^S$:

$$P_{c,t}^S = \sum_{\tau=1}^{\infty} \frac{V_{s,t}^S}{Q_s^S}(\bar{r}_{s,t}^S + 1 - m_S)\frac{m_S^{\tau-1}}{(1+r_{s,t}^S)^\tau} = \frac{V_{c,t}^S}{Q_s^S}\frac{\bar{r}_{s,t}^S + 1 - m_S}{r_{s,t}^S + 1 - m_S} \tag{2.43}$$

The interest rate and the price of bank bonds are determined analogously to those of nb-securities. The main difference is that the quantity of bonds is not constant but endogenously determined. Furthermore, we assume that the inventory of bank bonds of the market maker cannot be negative, i.e. short sales of bank bonds are not allowed. The bond interest rate is updated as follows:

$$\log(r^B_{c,t+\frac{\phi}{\Phi_t}}) = \log(r^B_{c,t+\frac{\phi-1}{\Phi_t}}) - g^{MMB}\left(\frac{\sum_{A=1}^{N^B} \mathbf{\Delta Q^B_{c,t+\frac{\phi-1}{\Phi_t},\mathrm{A}}}}{\sum_{A=1}^{N^B} |\mathbf{\Delta Q^B_{c,t+\frac{\phi-1}{\Phi_t},\mathrm{A}}}|}\right), \tag{2.44}$$

where $g^{MMB} > 0$ is the bond impact factor and

$$\mathbf{\Delta Q^B_{c,t+\frac{\phi-1}{\Phi_t}}} = (-Q^{MMB}_{c,t}, \Delta Q^B_{c,t+\frac{\phi-1}{\Phi_t}}, \Delta Q^B_{1,c,t+\frac{\phi-1}{\Phi_t}}, ..., \Delta Q^B_{n^I,c,t+\frac{\phi-1}{\Phi_t}}, \Delta Q^B_{row,c,t+\frac{\phi-1}{\Phi_t}})'$$

is a vector of length $N^B = 3 + n^I$ containing the quantities of bonds being traded. The bond inventory of the market maker is given by $Q^{MMB}_{c,t} = m_B Q^{MMB}_{c,t-1} + (\Delta B_{c,t}/P^B_{c,t}) - \sum_{i=1}^{n^I} \Delta Q^B_{i,c,t} + \Delta Q^B_{row,c,t}$. The quantity $\Delta Q^B_{c,t}$ is the additional quantity of long-term loans the cb-agent c issued in period t. The price of a bank bond is again derived from the present value approach:

$$P^B_{c,t} = \sum_{\tau=1}^{\infty} \frac{B_{c,t}}{Q^B_{c,t}}(\bar{r}^B_{c,t} + 1 - m_B)\frac{m_B^{\tau-1}}{(1+r^B_{c,t})^\tau} = \frac{B_{c,t}}{Q^B_{c,t}}\frac{\bar{r}^B_{c,t} + 1 - m_B}{r^B_{c,t} + 1 - m_B} \tag{2.45}$$

We let the number of iterations in period t, Φ_t, be dependent on the discrepancy between supply and demand for overnight interbank loans, bonds and nb-securities. The trade-off between these discrepancies and simulation time is modeled by the following stopping criteria:

$$x^I \geq \operatorname*{median}_c \left(\frac{\left|I_{c,t+\frac{z^I-1}{z^I}} - \sum_{i=1}^{n^I} I_{i,c,t+\frac{z^I-1}{z^I}}\right|}{\max\left\{I_{c,t+\frac{z^I-1}{z^I}}, \sum_{i=1}^{n^I} I_{i,c,t+\frac{z^I-1}{z^I}}\right\}}\right) \tag{2.46}$$

$$x^{MMS} \geq \frac{1}{n^S}\sum_{s=1}^{n^S}\left|\frac{\sum_{A=1}^{N^S} \mathbf{\Delta Q^S_{s,t+\frac{z^S-1}{z^S},\mathrm{A}}}}{\sum_{A=1}^{N^S} |\mathbf{\Delta Q^S_{s,t+\frac{z^S-1}{z^S},\mathrm{A}}}|}\right| \tag{2.47}$$

$$x^{MMB} \geq \frac{1}{n^C}\sum_{c=1}^{n^C}\left|\frac{\sum_{A=1}^{N^B} \mathbf{\Delta Q^B_{c,t+\frac{z^B-1}{z^B},\mathrm{A}}}}{\sum_{A=1}^{N^B} |\mathbf{\Delta Q^B_{c,t+\frac{z^B-1}{z^B},\mathrm{A}}}|}\right| \tag{2.48}$$

with z^I, z^S and z^B defining the lowest iteration count for which the respective stopping criteria is fulfilled. In essence, a satisfactory balance between demand

and supply of overnight loans, nb-securities and bonds is achieved when the median or average of the relative discrepancy between supply and demand does not exceed x^I, x^{MMS} and x^{MMB}, respectively. Since all three stopping criteria have to be fulfilled simultaneously, the pricing mechanism terminates after $\Phi_t := \max\{z^I, z^S, z^B\}$ iterations.

2.7 Modeling The Liquidity Coverage Ratio

The liquidity coverage ratio (LCR) is part of the Basel III framework and has been designed in order to address the problem of insufficient liquidity in times of stress. Specifically, the regulation requires banks to hold sufficient high quality liquid assets (HQLA) in order to meet the expected net cash outflows over thirty days of stress. The stress scenario is thereby defined by the regulator via fixed run-off rates for liabilities, inflow rates for assets that do not count as HQLA and haircuts for assets that count as HQLA. The run-off rate and the inflow rate specify how much of the liabilities and assets cannot be rolled over in times of stress, whereas the haircut implies a potential loss in value of a HQLA in times of stress. The regulation that should be fully implemented by 2019 (2018 in the European Union) requires that in normal times the ratio of HQLA to net outflows is greater than or equal to one, i.e.

$$\text{LCR} = \frac{\text{HQLA}}{\text{net outflows of 30 days}} \geq 100\% \tag{2.49}$$

Basel III (2013) is our source for how the assets and liabilities of the banks in our model would be treated under the LCR regulation.

2.7.1 Commercial Banks

The only asset of a cb-agent that qualifies as a high quality liquid asset is cash. Under the LCR, cb-agents need to hold the following amount of cash:

$$C^{LCR}_{c,t} = \begin{cases} 0.25 \cdot \text{outflows}_{c,t} & \text{if inflows} > 0.75 \text{ outflows} \\ \text{outflows}_{c,t} - \text{inflows}_{c,t} & \text{if inflows} \leq 0.75 \text{ outflows} \end{cases} \tag{2.50}$$

Note that according to the LCR regulation, banks need to hold at least 25% of their outflows in HQLA. The outflows a commercial bank needs to consider result from potential withdrawals from customer deposits, bonds and overnight interbank debt, while the inflows consider the expected interest payments and repayments of loans. With the balance sheet identity from Eq. (2.6), the necessary volume of wholesale debt under the LCR regulation is given by:

$$W_{c,t} = L_{c,t} - E_{c,t} - D_{c,t} + C^{LCR}_{c,t}(a_{c,t}) \tag{2.51}$$

Note that under the LCR, the necessary volume of wholesale debt is dependent on the composition of wholesale debt.[25] The target share of long-term debt is therefore no longer determined by Eq. (2.9). When including Eq. (2.51) into

[25] See Appendix 2.10.8 for the complete specification of $W_{c,t}$

the calculation of the interest surplus of Eq. (2.10), the solution for the optimal maturity structure becomes more complex and needs to be solved numerically.

There are situations where it is sensible for a cb-agent not to comply with the LCR regulation. Whenever outflows from wholesale debt increase faster than the stock of HQLA itself, commercial banks are unable to the meet the LCR regulation and are allowed to temporarily hold less liquid assets than required. Furthermore, we allow agents to fall short of a LCR of 100% when they are unable to obtain sufficient wholesale funding and have to access the central bank's marginal lending facility. The implementations of the LCR regulation in different regions typically allow banks to be non-compliant under extraordinary circumstances. In such situations, a plan detailing how and when compliance with the LCR can be restored would need to be negotiated with the regulator.

2.7.2 Investment Banks

For ib-agents, the simplest way of complying with the LCR regulation at the bank level is to ensure that an investment in asset ζ is funded in a LCR-neutral way, i.e.:

$$\max\{0.25 \cdot \text{outflows}_{i,\zeta,t}, \text{outflows}_{i,\zeta,t} - \text{inflows}_{i,\zeta,t}\} = \text{HQLA}_{i,\zeta,t} \qquad (2.52)$$

Since HQLA in general have a low expected return, a reasonable assumption is that investment banks want to minimize their holdings of HQLA. Equation 2.52 thus holds with an equality.

In our model, nb-securities qualify as HQLA for which a haircut h^S needs to be applied. The possibility to count nb-security s as a liquid asset, however, depends on whether the asset is used as collateral or not. Only if the asset is not used as collateral in a repo transaction will it add to the stock of HQLA. Given that an nb-security in our model can be financed by repos and investor deposits, the problem of investment bank i is to determine the optimal share of repo financing $\alpha^R_{i,s,t}$ for each nb-security s. The optimal share is given by the $\alpha^R_{i,s,t}$ that satisfies Equation 2.52. Outflows for investments in nb-securities are thereby determined by the mix of repo financing and investor deposits as well as the respective parameters for run-off rates, maturity, interest rates and haircuts. HQLA are given by the value of nb-securities s after haircuts that are financed exclusively via investor deposits. When an asset is used as collateral or adds to the stock of HQLA, no inflows from that asset are considered under the LCR regulation. Since funding purchases of nb-securities exclusively with repos would cause an imbalance between outflows and HQLA, an implication of the LCR in our model is that investment banks agents will employ a mix of repos and investor deposits in financing nb-securities.[26]

While nb-securities qualify as HQLA, overnight interbank debt as well as bonds issued by commercial banks do not qualify as such. Funding investments in bank bonds and interbank loans therefore require complementary purchases of HQLA. This implies that the investor deposits needed to finance one unit of a bond or a overnight interbank loan from agent c will be $x^B_{i,c,t}$ and $x^I_{i,c,t}$, respectively, times larger than they would be without the LCR. As in the case of nb-securities, the optimal values for $x^B_{i,c,t}$ and $x^I_{i,c,t}$ satisfy Equation 2.52.

[26]Without the LCR, ib-agents would only use the funding instrument with the lowest haircut (see Equation 2.21)

Outflows for both assets are thereby determined by the volume of investor deposits that is used to finance both the asset and the HQLA as well as the run-off rate, maturity parameter, interest rate and haircut of investor deposits. Inflows are given by the expected interest and principal payments of bank bonds and overnight interbank loans, which in turn depend on expected default rates, interest rates and the maturity parameters for the asset. Since it faces no haircut under the LCR, we assume that investment banks only use cash as the HQLA in these transactions.

$$a^R_{i,s,t} = \begin{cases} -(1-h^R_{s,t})a^S_{i,s,t}\alpha^R_{i,s,t} & \text{if } a^S_{i,s,t} \geq 0 \\ 0 & \text{else} \end{cases} \tag{2.53}$$

$$\begin{aligned} a^D_{i,t} =& -(1-h^D_{i,t})\Bigg(a^I_{i,t}(1+(1-h^D_{i,t})(x^I_{i,t}-1)) + \sum_{c=1}^{n^C} a^B_{i,c,t}(1+(1-h^D_{i,t})(x^B_{i,c,t}-1)) + \\ &+ \sum_{s\in\mathcal{D}} a^S_{i,s,t}(1-\alpha^R_{i,s,t})\Bigg), \end{aligned} \tag{2.54}$$

with $\mathcal{D} := \{s|a^S_{i,s,t} \geq 0\}$.[27]

2.8 Simulations

The simulations presented in this paper are conducted with an uncalibrated model, which implies that only qualitative inferences are feasible in the current setup. All parameters and initial values are reported in Tables 2.4 and 2.5 of the appendix. We simulate the model with $n^C = 100$ cb-agents, $n^I = 30$ ib-agents and $n^S = 15$ nb-securities.[28] Nb-securities should not be interpreted as individual assets, but rather as large portfolios of assets. We assume that ib-agents, although fewer in number, are larger than cb-agents in terms of balance sheet size (induced by a larger equity target). Customer deposits are kept rather low (5 times the equity target) in order to evoke a market for wholesale funding. This is consistent with the capital structure of large commercial banks in reality. The fluctuations in customer deposits are set to represent a rather calm economic environment. This also applies to the other two exogenous stochastic processes: the default rates for loans to the real sector and default probabilities of nb-securities. We thereby want to reproduce the seemingly stable financial system prior to the financial crisis. Each simulation run lasts for $T = 2000$ periods, whereby we discard the first 750 periods in order to reduce the impact of initial values. Each period represents a trading day and 250 periods a trading year.

In order to assess the impact of the liquidity coverage ratio (LCR) regulation, we compare the results of simulations under two different setups: the benchmark setup without the liquidity coverage ratio and the LCR setup that includes the extensions of the model introduced in Section 2.7. Simulations within each setup are repeated 20 times. While the random seeds for the stochastic elements differ

[27]See Appendix 2.10.8 for the calculations of $\alpha^R_{i,s,t}$, $x^B_{i,c,t}$ and $x^I_{i,t}$.

[28]The number of agents and nb-securities seems low when compared to reality. However, taking into account, for example, that in the EU the largest 5% of banks (approximately 140 institutions) held about 90% of total banking assets in 2006, makes the choice appear more realistic.

for the 20 simulation runs within one setup, they are identical across setups. This facilitates the comparison of both setups and at the same time reduces the probability that the documented results are due to chance.

2.8.1 Impact On Balance Sheets

In Table 2.1 we report the ratios of balance sheet positions to total assets for cb-agents with and without the LCR. The ratios document average values across time, agents and simulation runs. In the column labeled "change", we report the difference between the balance sheet positions under the two setups divided by the volume of total assets under the benchmark setup. This allows for a comparison of levels in addition to a comparison of ratios. Beside the level of customer deposits, which is exogenous to the model, all differences in levels are highly significant. The standard deviations, reported in parenthesis, describe the variation in the respective balance sheet ratios across simulation runs.

Table 2.1: Average balance sheet of a cb-agent

	without LCR	with LCR	change
	[% total assets]	[% total assets]	[% to benchmark]
loans	99.52	96.99	-2.14
	(0.06)	(0.21)	
cash	0.48	3.01	+540.71
	(0.06)	(0.21)	
equity	5.23	5.17	-0.75
	(0.02)	(0.03)	
deposits	30.46	30.33	0.00
	(0.37)	(0.44)	
overnight interbank	8.05	0.45	-94.41
	(0.84)	(0.13)	
bonds	56.27	63.83	+13.92
	(1.09)	(0.56)	
total assets	100.00	100.00	+0.41

Note: This table documents average balance sheet ratios across time, cb-agents and simulation runs for simulations with and without the LCR. The numbers in parentheses are standard deviations and capture the variation in the balance sheet ratios across simulation runs.

The most striking impact of the LCR on balance sheet ratios is unsurprisingly the change in the cash position, which represents the high quality liquid asset (HQLA) within our framework. While cb-agents try to avoid cash holdings in the benchmark setup, they are obliged to hold cash when complying with the LCR regulation. Although the relative change in cash holdings is very large (over 540%), the mean cash to total asset ratio under the LCR setup is only slightly higher than three percent.[29] Interestingly, the increase in HQLA (cash) leads to a 2.14% decrease in the level of loans the mean commercial bank

[29]In reality, there may be several reasons for commercial banks to hold liquid assets even without any liquidity regulation. The provision of credit lines to households or firms, for example, would be a good reason to hold a stock of HQLA on the balance sheet. Also, meeting reserve requirements will lead banks to hold HQLA.

provides to the real sector.[30] This is not a trivial result, since the observed substitution effect could have been avoided by a sufficiently large expansion of agents' balance sheets. The observed increase in balance sheet size (+0.41%) is not enough to avoid a reduction in loans when compared to the benchmark setup. Balance sheets can be expanded by taking on more debt (i.e. a lower equity to total assets ratio), which does not necessarily mean that risk increases under the LCR setup. Since cash cannot lose value in our model, expanding the asset side with cash does not add any risk. On the liabilities side, however, the refinancing risk may increase when the expansion is financed with wholesale debt, in particular overnight wholesale debt. The negative change in the level of equity (-0.75%) suggests that cb-agents have become less profitable under the LCR regulation. This is due to higher wholesale funding costs, which are induced by a drastic change in the funding structure of cb-agents under the LCR setup. The overnight interbank market almost completely breaks down and overnight debt is replaced by longer term bank bonds, which increase by 13.92%. When the LCR is binding, it becomes impossible to finance long-term illiquid assets with overnight debt. Since the return of cash holdings is lower than the interest rate on overnight debt, the interbank market breaks down. The increased demand for long-term wholesale funding leads to increasing funding costs (interest rates of bank bonds increase by about 15 basis points) as documented in Table 2.3. In general, we would assume that the LCR will shift demand towards funding sources with higher maturity and thereby steepen the term structure of uninsured wholesale debt.[31]

Table 2.2 compares the balance sheet ratios under the benchmark setup and the LCR setup for the mean ib-agent.[32] Through the interaction with cb-agents, ib-agents decrease their overnight interbank lending and increase their holdings of bank bonds. The higher interest rate on bank bonds increases the profitability of the mean ib-agent, which leads to a higher level of equity when compared to the benchmark case. While the higher ratio of cash to total assets reduces the risk of the asset side, the shifting from overnight interbank loans to long-term bank bonds increases risk. In sum, the unchanged equity to total assets ratio suggests that the reallocation of assets has been risk neutral. The increase in balance sheet size by 1.55%, which is due to the higher profitability of ib-agents has also led to an increase in nb-security holdings. This leads to a decrease in the interest rate of nb-securities (see Table 2.3). Lower interest

[30] Impact assessments that rely on statistical relationships in historical data also suggest that the LCR regulation will tend to decrease loan supply. Estimated impacts range from 3–5% (see Figure 3-7 in Office of Financial Research, 2014).

[31] Bech and Keister (2017) derive a similar conclusion with a different method. They introduce the LCR regulation into a standard model of banks' reserve management and find that the short end of the yield curve tends to get steeper when banks are concerned about violating the LCR. Furthermore, statistical impact assessments of the LCR regulation, summarized in Office of Financial Research (2014), predict increases in interest rates between 15 and 30 basis points.

[32] Ib-agents in our model can represent the investment banking arm of a commercial bank, but also an institution (e.g. a hedge fund, broker dealer, structured investment vehicle, etc.) that is part of the shadow banking system and therefore not subject to normal financial regulation. In the following, we assume that the LCR applies for all ib-agents. Qualitatively, most results remain valid when the LCR is only applied to cb-agents. An exception is the shift in the investment bank funding structure towards a higher ratio of investor deposits and a lower ratio of repo financing, which disappears when ib-agents do not need to comply with the LCR regulation.

Table 2.2: Average balance sheet of an ib-agent

	without LCR [% total assets]	with LCR [% total assets]	change [% to benchmark]
non-bank-securities	84.40	83.21	+0.12
	(0.38)	(0.43)	
cash	3.50	4.71	+36.77
	(0.18)	(0.19)	
bank bonds	10.20	11.46	+14.10
	(0.27)	(0.26)	
interbank loans	3.96	0.00	-99.99
	(0.14)	(0.00)	
margin account	0.60	0.61	+4.85
	(0.05)	(0.04)	
equity	3.96	3.96	+1.56
	(0.17)	(0.15)	
investor deposits	11.05	23.32	+114.35
	(0.19)	(0.19)	
repos	84.39	72.10	-13.24
	(0.38)	(0.36)	
short sales	0.60	0.61	+4.85
	(0.05)	(0.04)	
total assets	100.00	100.00	+1.55

Note: This table documents average balance sheet ratios across time, ib-agents and simulation runs for simulations with and without the LCR. The numbers in parentheses are standard deviations and capture the variation in the balance sheet ratios across simulation runs.

rates means higher prices, which increases the fraction of agents that deem a specific nb-security to be overvalued. As a result, the volume of short sales and correspondingly the volume of cash held in the margin account increase.

Table 2.3: Average interest rates by category

	without LCR [% per year]	with LCR [% per year]	change [% to benchmark]
non-bank-securities	0.035	0.033	-5.714
	(0.004)	(0.003)	
overnight interbank	1.417	0.209	-81.779
	(0.023)	(0.012)	
bank bonds	1.806	1.948	+7.290
	(0.028)	(0.033)	

Note: This table reports average interest rates by category for simulations with and without the LCR. The numbers in parentheses are standard deviations and capture the variation in the interest rates across simulation runs.

2.8.2 Impact On The Maturity Of Wholesale Funding

The maturities of assets and liabilities are important inputs for calculating the liquidity coverage ratio. All else being equal, shorter maturities of loans to the real sector would increase the inflows and reduce the volume of HQLA required under the LCR regulation. Shorter maturities of wholesale debt, on the other hand, would increase outflows and lead to a higher demand for HQLA. It is therefore plausible that banks will consider changing the average maturity of their assets and/or liabilities when the LCR regulation is active. Unlike the choice between overnight interbank debt and long-term wholesale debt (bank bonds), the average maturity m_B of bank bonds is exogenous to our model. In order to test whether cb-agents will be inclined to choose a different maturity structure for their bank bonds, we compare simulation results for different values of the maturity parameter m_B under the benchmark setup and the LCR setup. We assume that agents have an incentive to change their maturity structure if they can profit from such a change.

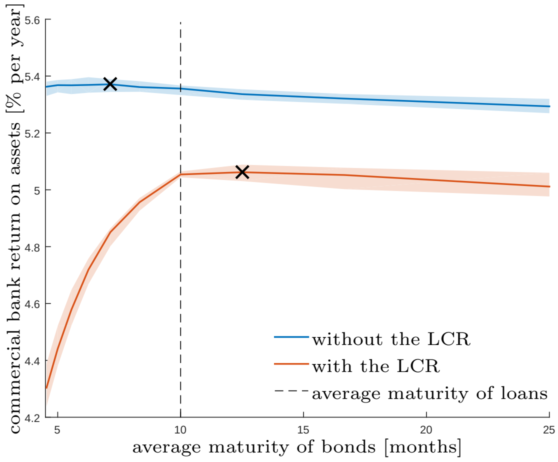
In Figure 2.2, we show the relation between the return on assets (RoA) of cb-agents and the average maturity[33] of their long-term wholesale funding (bonds). The solid lines represent the mean values over time, agents and simulation runs, while the shaded areas depict the variation (specifically, the 90% confidence interval) across simulation runs. The dashed line represent the average maturity of loans, which is kept constant, and the Xs mark the average maturity for which the RoA is maximized. Figure 2.2 reveals three important findings: First, cb-agents are on average always more profitable under the benchmark setup than under the setup where the LCR is binding. Second, when the average maturity

[33] The average maturity in months is computed as

$$\int_1^\infty (1 - m_L) m_L^{t-1} t \delta t = \frac{(m_L - 1)(\log(m_L) - 1)}{\log(m_L)^2}.$$

We assume that a month has 20 trading days.

Figure 2.2: Commercial bank profit for different maturities of bank bonds



Note: This figure shows the average return on assets of cb-agents for different average maturities of bank bonds. Solid lines represent average returns on assets across cb-agents, time and simulation runs. Shaded areas depict the variation in average returns on assets – averaged across cb-agents and time – across simulation runs. The lower and upper bounds of the shaded areas are the 10th and 90th percentiles, respectively, of the average return on assets across cb-agents and time. The dashed line represents the average maturity of loans, which is kept constant, and the Xs mark the average maturity for which the average return on assets is maximized.

of bank bonds is greater than the average maturity of loans ($m_B > m_L$), the spread between the RoAs of the two setups remains more or less constant. The spread, however, widens dramatically when $m_B < m_L$. Third, the optimal average maturity of bank bonds under the benchmark setup is shorter than the average maturity of loans. The opposite is true under the LCR setup.

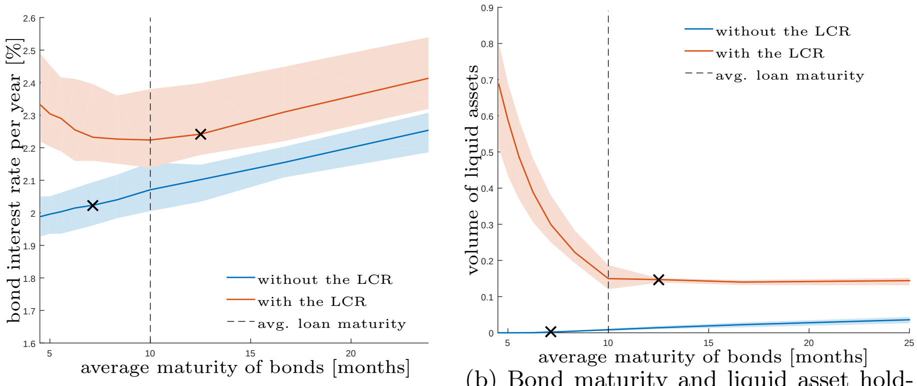
The third finding suggests that a commercial bank under the LCR regulation will have a considerable incentive to make sure that its wholesale funding has on average a greater maturity than the average maturity of its assets. This can be achieved either by increasing the maturity of bank bonds or decreasing the maturity of loans to the real sector. In both cases, banks would reduce the liquidity in the banking sector. Beside risk transformation, liquidity creation, which is achieved when banks' liabilities are more liquid than their assets, has been acknowledged as an important role of banks in the context of economic growth at least since Adam Smith (see Berger and Bouwman, 2009). Our model suggests that liquidity creation with wholesale debt will become more difficult when banks need to comply with the LCR regulation.[34]

The first and second findings are explained by Figure 2.3: As illustrated in the left panel, bond interest rates under the LCR setup are persistently higher than in the benchmark setup, which explains the lower profitability of cb-agents.[35] For $m_B \geq m_L$ bond interest rates increase with increasing average

[34]Empirical evidence supports this model prediction. At least in the US, the funding structure of banks is undergoing changes in line with our simulation results. Wholesale funding is becoming increasingly longer term, while banks are increasing their volume of liquid assets and are providing fewer loans to the real sector (see e.g. Buehler et al., 2013).

[35]Note that the specific result that interest rates are higher under the LCR and the general result that interest rates increase with increasing maturity are emergent phenomena of our model. These results are not explicitly written into the model equations, but emerge through

Figure 2.3: Bond interest rates and commercial bank liquid asset holdings for different maturities of bank bonds



(a) Bond maturity and bond interest rates

(b) Bond maturity and liquid asset holdings

Note: This figure shows average bond interest rates and average commercial bank liquid asset holdings for different average maturities of bank bonds. The solid lines represent average bond interest rates (Figure 2.3a) and average liquid asset holdings (Figure 2.3b) across cb-agents, time and simulation runs. The shaded areas depict the variation in average bond interest rates and cb-agents' average liquid asset holdings – both averaged across cb-agents and time – across simulation runs. The lower and upper bounds of the shaded areas are the 10th and 90th percentiles, respectively, of the respective distributions. The dashed lines represent the average maturity of loans, which is kept constant, and the Xs mark the average maturities for which the average return on assets is maximized.

maturity of bonds under both setups. The upward-sloping yield curve emerges due to risk considerations by ib-agents. The longer the average maturity, the smaller will be the received repayment per period. When repayments are spread over a longer time horizon, it becomes more probable that the investor will suffer losses due to a default event or a reassessment of default probabilities. Ib-agents seek compensation for this through higher interest rates. Expectations of lower or higher interest rates in the future do not play a role in our current setup. When cb-agents under the LCR setup choose an average maturity for their wholesale funding that is lower than the average maturity of loans, interest rates start increasing with declining m_B. A demand effect explains this result. As illustrated in the right panel of Figure 2.3, cb-agents need to hold an increasing volume of cash for very low average maturities of wholesale debt. Consequentially a higher volume of wholesale debt is needed to fund the same amount of loans to the real sector. This leads to higher interest rates. The increasing spread between the RoAs in Figure 2.2 for $m_B < m_L$ is thus partially

the interactions of agents in the market. The lower profitability level under the LCR, on the other hand, is not a purely emergent phenomena. It is partly due to our modeling choice of not allowing cb-agents to endogenously change the interest rate on loans to the real sector. This makes the model prediction that profitability will suffer under liquidity regulation weaker than the prediction that interest rates of long-term wholesale debt will increase. Banks could restore their profitability in light of higher funding costs by increasing the interest rate they charge on loans. We refrain from allowing such adjustments in the current setup because the real sector is not endogenous and can itself not react to changing interest rates. Nevertheless, we assume that the decline in volume of loans provided to the real sector under the LCR regulation (see Table 2.1) holds, since rising interest rates on loans would reduce the demand for loans.

explained by the higher interest rate for wholesale debt and partially by the higher share of low-yielding HQLA on the balance sheets of cb-agents.

2.8.3 Impact Of A Confidence Shock

Our analysis so far has shown that a binding LCR regulation will pressure banks to make changes to the structure of their balance sheet. The principal aim of the regulator is that these changes will contribute to stabilizing the financial system. In order to filter out the impact of the regulation on the stability of the system, we compare the dynamics that are triggered by a controlled shock in the benchmark setup and the LCR setup.[36] The focus of the following analysis lies on explaining the impact of the LCR regulation on the stability of banks' loan supply to the real sector.

The default of Lehman Brothers in September 2008 led to a surge in uncertainty about the solvency of banks. We want to model a mutual loss of confidence in the banking sector by shocking the expectations ib-agents have about the default probabilities of cb-agents. Specifically, we multiply the expectation $\mathrm{E}_i[\Omega_c^C]$ (see Eq. (2.32)) with a factor to obtain the shocked expectation $\mathrm{E}_i^{\mathrm{sh}}[\Omega_c^C]$, which lasts for 30 trading days before returning to its normal level. The left panel of Figure 2.4 shows the impact of the shocks on the average loan portfolio of cb-agents in the benchmark setup. Two intensities of the confidence shock are plotted. The blue line graphs the percent difference between the shocked and unshocked system when default probability expectations are doubled, while the red line draws that difference for a tenfold increase in expected default probabilities. For both shock intensities, the loan supply decreases immediately after the shock and starts to rise again after 30 days. However, the decrease of loan supply as well as its subsequent recovery is steeper for the weaker shock than for the stronger shock. Noteworthy is also the belly that the loan supply displays for the more severe shock, which lasts for approximately three years (from 0.5 to 3.5 years after the shock). It implies that short lived but intense confidence crises in the financial sector can have a sustained effect on the real economy. The implementation of the liquidity coverage ratio aggravates the adverse effects of confidence shocks on the loan supply, as illustrated in Figure 2.4b. While the cumulative difference between the loan supply in the benchmark setup and the LCR setup quickly becomes irrelevant for the weak confidence shock, it is substantial for the larger shock.[37] One year after the shock, cb-agents in the LCR

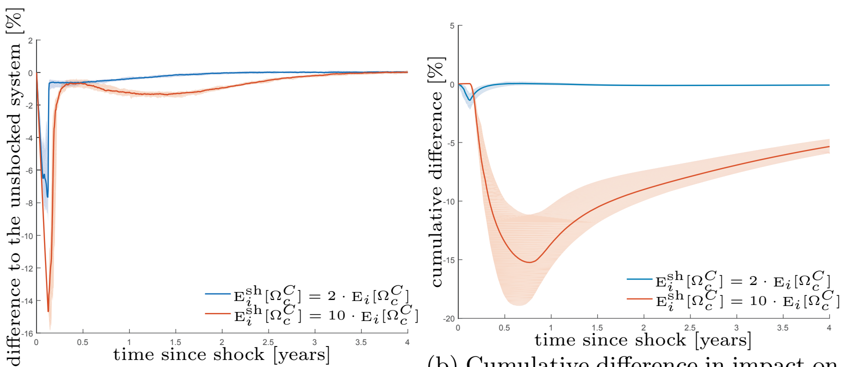
[36] Financial stability in the context of the LCR regulation does not feature prominently in the literature. One exception is van den End and Kruidhof (2013), who argue for a flexible LCR requirement in order to mitigate negative side effects such as fire sales during times of stress. Relatedly, many observers have raised concerns that even though the regulator explicitly allows banks to temporarily fall below minimum requirements when stressed, they may be reluctant to do so in reality (see e.g. Stein, 2013). Similar to the stigma associated with accessing the discount window (see e.g. Armantier et al., 2015), banks may fear a loss of reputation when having to report that their LCR falls short of 100%. In our model, cb-agents draw down their HQLA in times of stress. Technically, whenever they fail to refinance wholesale debt and need liquidity assistance from the central bank, they reduce their HQLA before accessing the marginal lending facility. There are no reputational costs associated with this behavior.

[37] The cumulative difference CD_t is computed as follows:

$$\mathrm{CD}_t = \frac{\left(\sum_{\tau=1}^{t} \Delta L_\tau^{\mathrm{LCR,s}} L_\tau^{\mathrm{Bench,u}}\right) - \left(\sum_{\tau=1}^{t} \Delta L_\tau^{\mathrm{Bench,s}} L_\tau^{\mathrm{Bench,u}}\right)}{\sum_{\tau=1}^{t} L_\tau^{\mathrm{Bench,u}}},$$

setup provided almost 15% less loans to the real sector than their counterparts in the benchmark setup. The consequence is likely to be a severe recession.

Figure 2.4: Impact of a confidence shock on the supply of loans to the real sector



(a) Impact on loans in the benchmark setup

(b) Cumulative difference in impact on loan supply between the LCR setup and the benchmark setup

Note: This figure shows the impacts of confidence shocks of two intensities on the supply of loans to the real sector. The left panel shows the impacts of the two confidence shocks in the setup without the LCR. The right panel shows comparisons between the cumulative impacts of the two confidence shocks in the setup without the LCR and in the setup with the LCR. Solid lines represent average values across cb-agents and simulation runs. Shaded areas depict the variation in the differences across simulation runs, where the lower and upper bounds of the shaded areas are the 10th and 90th percentiles, respectively, of the respective distributions.

Although the temporary loss of confidence in the solvency of cb-agents triggers the decline in loan supply, the stability of cb-agents is not compromised as a consequence of the shock.[38] Figure 2.5a shows that the extent to which commercial banks' equity in the shocked benchmark scenario deviates from the unshocked system is rather small. The deviation is explained by changing funding costs, depicted in Figure 2.5c. Ib-agents react to their perception of higher default probabilities by increasing interest rates of wholesale debt. Since overnight debt needs to be rolled over every trading day, higher interest rates immediately show up in funding costs in the benchmark setup and cause the initial drop in equity seen in Figure 2.5a. Then, as cb-agents shrink their balance sheet by reducing their loan supply, average funding costs temporarily decline, which increases profitability and hence equity. After the shock is resolved and default probability expectations normalize, ib-agents reduce the interest rates on wholesale debt. However, for some months they remain higher than they would have been without the shock (see bond prices in Figure 2.8a). In part, this is the case because unexpected events influence the risk assessment of agents by raising their awareness about the potential faultiness of their expectations.[39]

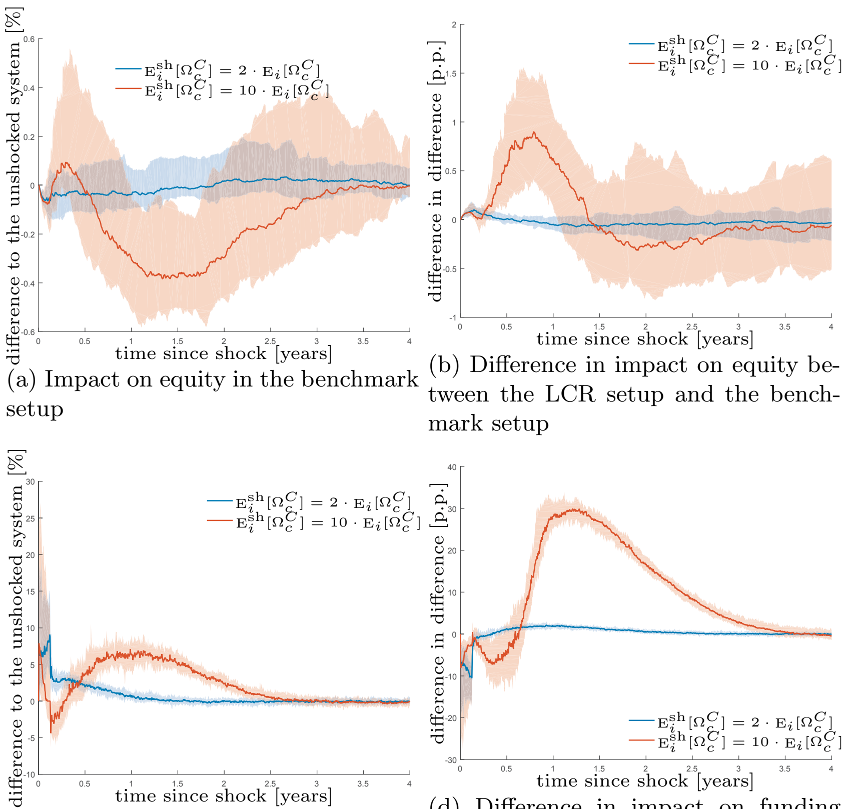
with $\Delta L_\tau^{\mathrm{LCR,s}}$ and $\Delta L_\tau^{\mathrm{Bench,s}}$ being the percentage difference of the average loan supply for the shocked LCR setup and benchmark setup, respectively. $L_\tau^{\mathrm{Bench,u}}$ denotes the average amount of loans supplied for the unshocked benchmark setup. With such a calculation of the cumulative difference, we assume that the loan supply in the unshocked case is equal for the benchmark setup and the LCR setup.

[38] It is important to note that the lack of any feedback between the real sector and the financial sector is an issue here. Typically, recessions are accompanied by a deterioration of credit quality, which would have an impact on the solvency of commercial banks.

[39] Technically, the increased prudence in response to a shock is introduced through the

The increased cost for wholesale debt explains why approximately half a year after the shock the equity level of cb-agents falls below the level measured in the unshocked system. Note that because payment conditions for wholesale debt are defined for its entire duration, average funding costs return to their normal (unshocked) level after three years, while bond prices already normalize after approximately ten months.

Figure 2.5: Impact of a confidence shock on cb-agents' equity and average funding costs



(a) Impact on equity in the benchmark setup

(b) Difference in impact on equity between the LCR setup and the benchmark setup

(c) Impact on refinancing costs in the benchmark setup

(d) Difference in impact on funding costs between the LCR setup and the benchmark setup

Note: This figure shows the impacts of confidence shocks of two intensities on cb-agents' equity and funding costs. The left panels show the impacts of the two confidence shocks in the setup without the LCR. The right panels show comparisons between the impacts of the two confidence shocks in the setup with the LCR and in the setup without the LCR. Solid lines represent average differences across cb-agents and simulation runs. Shaded areas depict the variation in differences across simulation runs, where the lower and upper bounds of the shaded areas are the 10th and 90th percentiles, respectively, of the respective distributions.

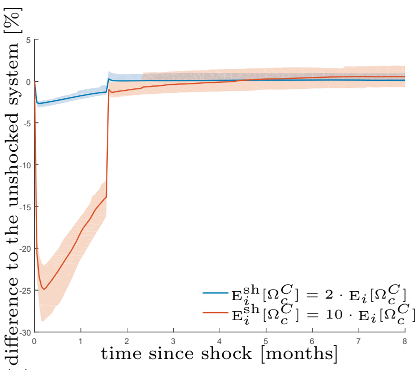
Unlike its impact on loan supply, the LCR regulation has a positive effect on cb-agents' equity for the first one and a half years after the shock. Figure 2.5b graphs the percentage point difference of the changes in equity capital with

inclusion of past forecast errors into ib-agents' expectations of variance (see Eq. (2.36). The parameter ψ^B thereby insures that large misjudgments remain in memory for some time.

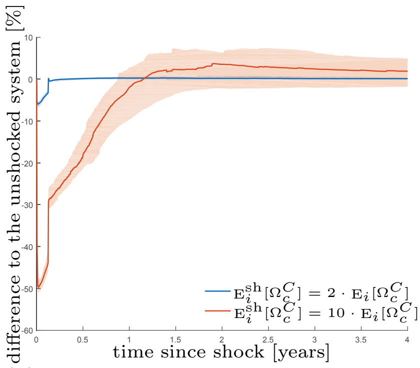
respect to the unshocked system between the LCR setup and the benchmark setup. The differences in the two impacts of the shock on equity can be explained by looking at the difference in changes to the funding costs under the two setups, which is illustrated in Figure 2.5d. A higher share of long-term wholesale debt under the LCR setup implies that less debt needs to be rolled over when interest rates sharply increase in response to the confidence shock. Therefore, average funding costs rise less quickly when commercial banks comply with the LCR regulation. This is despite the fact that bond prices fall below their counterparts in the benchmark setup (see Figure 2.8b). However, as soon as cb-agents stop deleveraging and start expanding their loan portfolios, the higher bond interest rates increase overall funding costs. Consequentially, equity falls under the level displayed in the benchmark setup.

Cb-agents' equity levels and funding costs apparently do not explain the detrimental effect the liquidity coverage ratio regulation has on the loan supply to the real sector. The dynamics of equity of ib-agents are more instructive. If ib-agents' balance sheets remain unconstrained during the shock, we would expect that the symmetry of the confidence shock (i.e. the initial increase in expected default probability is fully reversed after 30 periods) will lead to short-lived implications of the shock. Any initial detrimental effect should be followed by a beneficial effect of similar magnitude as expectations of cb-agents' default probabilities normalize. Indeed, this is what we find under the benchmark setup. Figure 2.6a plots the impact of the confidence shocks on investment bank equity under the benchmark setup. When expectations of cb-agents' default probability increases, ib-agents suffer valuation losses. In case of the large shock, equity decreases by almost 25% at first, but starts to recover immediately with increasing bond prices (see Figure 2.8a). As confidence is restored after 30 days, equity reaches a level that is only slightly below the level measured in the benchmark setup without the shock. After approximately four months any trace of the confidence shock disappears. Although the recovery of ib-agents' equity under the large confidence shock is rather swift, there is a noticeable relation between the speed of the recovery and the shock size. This relation is more salient under the LCR setup. Figure 2.6b shows that while the impact of the small shock on equity appears very similar under both setups (it is slightly worse under the LCR setup), the impacts of the large shock have a different quality in the two setups. Under the LCR setup, the initial drop in equity is about 25 percentage points deeper and the resolution of the shock after 30 days lifts equity to a level that is still almost 30 percent below its unshocked counterpart. It takes more than a year before equity reaches and then surpasses the level measured under the LCR setup without the confidence shock. The stronger initial decline in equity can be explained by a stronger decline in bond prices, which drop on average approximately 8 percentage points below their counterparts in the benchmark setup (see Figure 2.8b). However, bond prices alone do not explain the qualitative difference in the impact on equity between the two setups. In particular, it needs to be explained why the symmetry between the initial detrimental effect of the shock and the subsequent beneficial effect of its resolution is broken.

Figure 2.6: Impact of a confidence shock on the equity of ib-agents



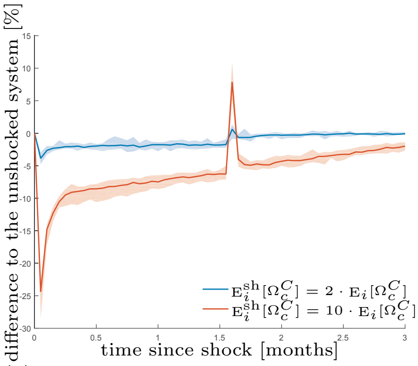
(a) Impact on equity in the benchmark setup



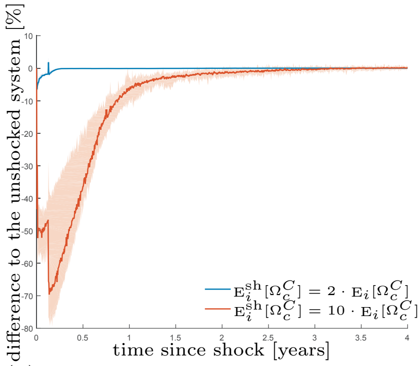
(b) Impact on equity in the LCR setup

Note: This figure shows the impacts of confidence shocks of two intensities on ib-agents' equity. The left panel shows the impacts of the two confidence shocks in the setup without the LCR. The right panel shows a comparison between the impacts of the two confidence shocks in the setup with the LCR and in the setup without the LCR. Solid lines represent average differences across cb-agents and simulation runs. Shaded areas depict the variation in differences across simulation runs, where the lower and upper bounds of the shaded areas are the 10th and 90th percentiles, respectively, of the respective distributions.

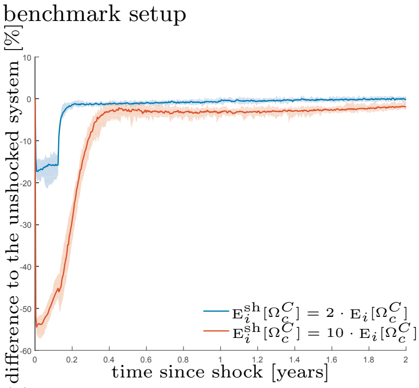
Figure 2.7: Impact of a confidence shock on ib-agents' balance sheet size and on the volume of investor deposits



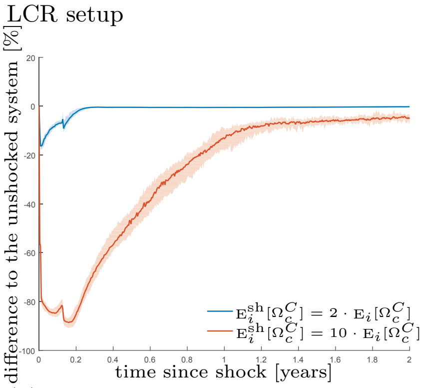
(a) Impact on balance sheet size in the benchmark setup



(b) Impact on balance sheet size in the LCR setup



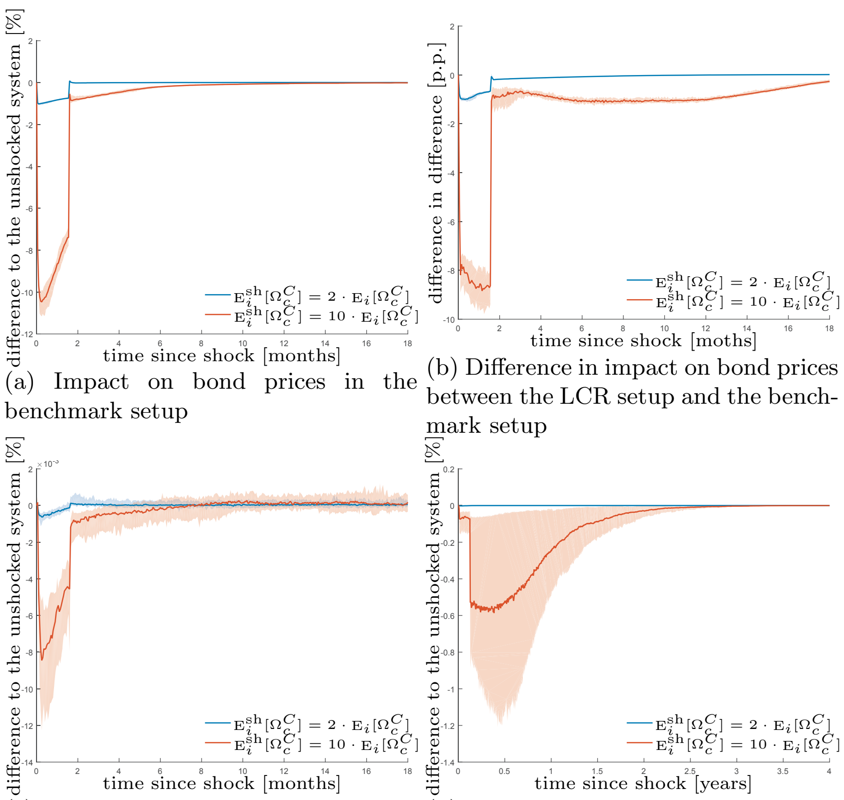
(c) Impact on investor deposits in the benchmark setup



(d) Impact on investor deposits in the LCR setup

Note: This figure shows the impacts of confidence shocks of two intensities on ib-agents' balance sheet size and on the volume of investor deposits. The left panels show the impacts of the confidence shocks in the setup without the LCR. The right panels show comparisons between the impacts of the two confidence shocks in the setup with the LCR and in the setup without the LCR. Solid lines represent average differences across cb-agents and simulation runs. Shaded areas depict the variation in differences across simulation runs, where the lower and upper bounds of the shaded areas are the 10th and 90th percentiles, respectively, of the respective distributions.

Figure 2.8: Impact of a confidence shock on average bank bond prices and average nb-security prices



(a) Impact on bond prices in the benchmark setup

(b) Difference in impact on bond prices between the LCR setup and the benchmark setup

(c) Impact on nb-security prices in the benchmark setup

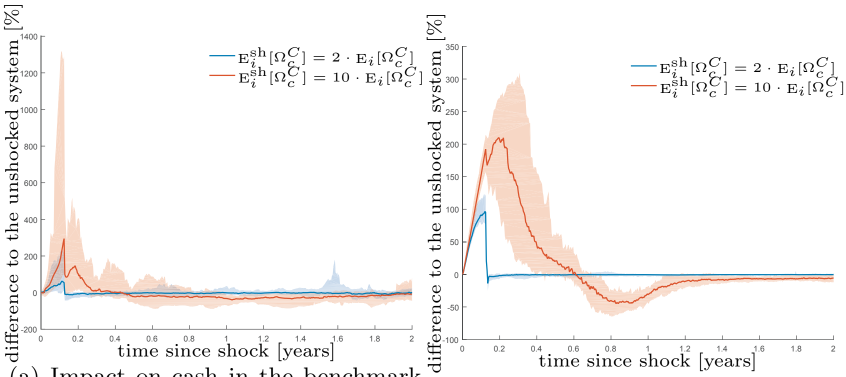
(d) Impact on nb-security prices in the LCR setup

Note: This figure shows the impacts of confidence shocks of two intensities on average bank bond prices and average nb-security prices. The left panels show the impacts of the confidence shocks in the setup without the LCR. The right panels show comparisons between the impacts of the two confidence shocks in the setup with the LCR and in the setup without the LCR. Solid lines represent average differences across cb-agents and simulation runs. Shaded areas depict the variation in differences across simulation runs, where the lower and upper bounds of the shaded areas are the 10th and 90th percentiles, respectively, of the respective distributions.

Figure 2.7a plots the average balance sheet size of ib-agents in response to the confidence shock in the benchmark setup. Due to the initial negative valuation effect, ib-agents start deleveraging, which leads to the observed contraction of balance sheets. The negative and positive peaks mark the first and last period of the shock, respectively. They are caused by overreactions of agents due to a temporary mispricing of assets. Nevertheless, the size of ib-agents' balance sheets quickly recovers. Figure 2.7b shows, on the other hand, that when banks comply with the LCR regulation the average size of balance sheets is first halved when the shock hits and then further decimated as the shock is resolved after 30 periods. While the first contraction of balance sheet size is a deliberate reaction to the decline in equity, the second seems counterintuitive. When expectations about cb-agents' default probabilities normalize, the positive valuation effect induced by rising bond prices raises equity and should thereby contribute to a normalization of balance sheet size. However, the fact that ib-agents have sold most of their portfolio in the wake of the shock dilutes the positive valuation effect from rising bond prices. At the same time, the price changes induced by both the shock and its resolution increase the volatility of ib-agents' earnings, which raises concerns among investors and leads them to withdraw their deposits, as illustrated in Figure 2.7d. The low level of funding at the time when the confidence shock is resolved furthermore has a peculiar effect on the prices of nb-securities. While they increase sharply after 30 days under the benchmark setup, they drop in the LCR setup (see Figure 2.8c and 2.8d). The reason for this can be derived from the portfolio optimization of ib-agents. Specifically, when the confidence shock is resolved, bank bonds become undervalued. As a result, ib-agents shift their scarce funding out of nb-securities and into bank bonds, which leads to the drop in nb-security prices. The valuation effect of this price drop further dilutes the positive valuation effect of rising bond prices. Our analysis suggests that the larger the confidence shock, the higher the asymmetry between the initial adverse effect of the shock on ib-agents and the ensuing beneficial effect when the shock is resolved. The circumstances that explain this growing asymmetry are accelerating investor deposit withdrawals, i.e. constrained balance sheets, and an increasing dilution of positive valuation effects.

Under the LCR setup and large enough confidence shocks, the asymmetry becomes increasingly destabilizing, at least with regard to cb-agents' loan supply to the real sector. The mechanism behind this destabilizing effect of the liquidity regulation is simple: The LCR incentivizes cb-agents to increase the maturity of their wholesale funding. The increased maturity makes ib-agents' bond holdings more prone to valuation effects, i.e. it increases risk. When shocks to cb-agents' perceived solvency are within the range of what ib-agents expect, the demanded higher interest rate compensates for the additional risk. The described asymmetry, however, causes unexpectedly strong adverse shocks to have a lasting impact on ib-agents' equity and balance sheet size. The consequential decline in the supply of cheap wholesale funding after the shock causes the subdued loan supply to the real sector. Put differently, by increasing the funding stability of cb-agents through the LCR regulation, the regulator deepens the contagion channel. The longer the maturity of tradable wholesale debt, the more immediate will be the transfer of stress between different bank business models.

Figure 2.9: Impact of a confidence shock on cb-agents' cash holdings



(a) Impact on cash in the benchmark setup

(b) Impact on cash in the LCR setup

Note: This figure shows the impacts of confidence shocks of two intensities on cb-agents' cash holdings. The left panel shows the impacts of the confidence shocks in the setup without the LCR. The right panel shows a comparison between the impacts of the two confidence shocks in the setup with the LCR and in the setup without the LCR. Solid lines represent average differences across cb-agents and simulation runs. Shaded areas depict the variation in differences across simulation runs, where the lower and upper bounds of the shaded areas are the 10th and 90th percentiles, respectively, of the respective distributions.

2.9 Conclusion

We have developed a model of the financial system that can be used as a test bed for banking regulation. The framework comprises the agents and institutions that have proved crucial in the propagation of the subprime mortgage shock in the U.S. into a global financial crisis. Specifically, we have modeled two agent types that represent commercial banks on one side, and investment banks and shadow banks on the other side. The agents of the model interact directly on wholesale debt markets and indirectly on asset markets. Beside a market for overnight interbank loans and long-term bank bonds, other funding sources include insured customer deposits, uninsured investor deposits, secured short-term debt in the form of repos as well as the possibility to borrow securities for the purpose of short selling. Credit to the real sector is the principal asset of cb-agents, while ib-agents specialize in trading securities, which may differ according to risk, maturity and market liquidity. We endow agents with sophisticated tools to manage the asset and liability sides of their balance sheet. Agents endogenously determine the size (i.e. leverage) and the structure of their balance sheets as well as their counterparties on the interbank market. Based on their expectations, agents try to behave optimally. Therefore they can quickly adapt to changing circumstances, which may arise endogenously or are enforced exogenously.

We employ our framework to assess the impact of the liquidity coverage ratio regulation on bank balance sheets, interest rates and financial stability. We find that the regulation will lead to a lower supply of bank loans to the real sector, higher interest rates, and a shift towards longer term wholesale funding. These findings are largely confirmed by existing empirical studies on the effects of liquidity regulations. Furthermore, we evaluate the impact of a confidence shock. A large and unexpected shock to confidence, which we model with a temporary increase in perceived default probability of cb-agents, leads to a severe credit crunch under the LCR regulation. While the regulation has a stabilizing effect on commercial banks, it decreases the stability of investment banks, who are the creditors of commercial banks in wholesale debt markets. A sustained decline in the supply of wholesale funding by ib-agents in response to the confidence shock is ultimately responsible for the credit crunch. In summary, we find that the LCR regulation does not feature a trade-off between the banking system's ability to provide loans to the real sector and financial stability. To the contrary, our results suggest that the LCR regulation negatively effects both.

We leave the calibration of our model to a real financial system to future research. A calibration of the model faces two major challenges. The first challenge is the complexity of the model, which has 39 parameters that characterize financial assets, balance sheet positions, the preferences of bank agents, expectation formation, and the behavior of exogenous agents. While some parameters can be estimated from micro data (e.g. equity targets or the maturity parameters for loans and nb-securities), the large majority has to be calibrated by matching the aggregate dynamics of our model to that observed in the data. The second challenge is data availability. Specifically, detailed information on the security and loan portfolios of financial institutions, the maturity structure of each of their assets and liabilities, and their bilateral relationships are not publicly available. However, some of this data are either already available or are beginning to become available at supervisory and regulatory institutions.

One major advantage of our framework is that it can be easily extended and modified to answer new research questions. Since the LCR regulation is only one of many banking regulations that were introduced with the Basel III reform package, a natural next step is an evaluation of the remaining regulations. How do these regulations affect the supply of bank loans to the real sector and financial stability in isolation? How do the results change when banks have to comply to different combinations of these regulations? How do the two Basel III liquidity regulations, i.e. the LCR and the Net Stable Funding Ratio, interact? Another interesting application of our framework, provided that it is calibrated to a real financial system, is stress testing. In stress testing, it is important to predict not only the first round effects of shocks but also subsequent effects resulting from the interplay between the behavioral responses of the financial institutions and the direct and indirect linkages between them. With its sophisticated decision making and risk management rules and the relevant direct and indirect transmission channels for shocks, our model is able to capture these effects.

2.10 Appendix

2.10.1 Initialization

Random variable	**Description**	**Distribution**	**Parameters**
Commercial Banks			
$\Delta D_{c,t}$	Change in customer deposits	Normal	$\mu_{c,t}^{\Delta D} = 0, \sigma_{c,t}^{\Delta D} = 0.001$
$\rho_{c,t}^{L}$	Loan default rate	Lognormal	$\mathrm{E}_{c,t}[\rho^L] = \frac{0.04}{250}, \mathrm{Var}_{c,t}(\rho^L) = (\frac{0.4}{250})^2$
$r_{c,t}^{W}$	Refinancing costs in commercial banks' value at risk calculation	Normal	Endogenous
Investment Banks			
$\epsilon_{i,j,t}^{\pi}$	Stochastic error term in forecasts of long-term profit rates	Normal	$\mu_{i,j,t}^{\epsilon^\pi} = \frac{0.05}{250}, \sigma_{i,j,t}^{\epsilon^\pi} = \frac{0.1}{250}$
$\epsilon_{i,c,t}^{\Omega}$	Stochastic valuation error of commercial banks' default probabilities	Normal	$\mu_{i,c,t}^{\epsilon^\Omega} = \frac{0.05}{250}, \sigma_{i,c,t}^{\epsilon^\Omega} = \frac{0.1}{250}$
$r_{j,t}^{S}$	Stock returns in calculation of repo haircuts and margin requirements	Normal	Endogenous

Table 2.4: Distribution assumptions

Category	Symbol	Description	Value
General Simulation Parameters	n^C	Number of commercial banks	100
	n^I	Number of investment banks	30
	n^S	Number of stocks	15
	T	Simulation Periods	2000
Commercial Banks			
General Parameters	E_c^*	Equity target	0.3
Asset Side Management	$\bar{r}_{c,t}^L$	Interest on loans	$\frac{0.07}{250}$
	m_L	Maturity of loans	0.995
	x^L	Confidence level in value at risk calculations	0.995
Liability Side Management	$r_{c,t}^D$	Interest paid on deposits	$\frac{0.001}{250}$
	m_B	Maturity of long-term debt	0.995
Raising short-term debt	γ_v	Elasticity of trust between the banks	0
	γ_u	Elasticity of relative attractiveness of the interest rate	1
	Ξ^{min}	Lower bound for aggregation mechanism transaction indicator Ξ	1
	Ξ^{max}	Upper bound for aggregation mechanism transaction indicator Ξ	20
Expectation Formation	ψ^I	Memory parameter in calculation of $\hat{\mathrm{E}}_{c,t}[a^{LLR}]$	0.1
	ψ^B	Memory parameter in calculation of $\hat{\mathrm{Var}}_{c,t}(r^B)$	0.1
	ψ^W	Memory parameter in calculation of $\hat{\mathrm{E}}_{c,t}[r_{total}^W]$, $\hat{\mathrm{Var}}_{c,t}(r_{total}^W)$	0.01
Investment Banks			
General Parameters	E_i^*	Equity target	4
Asset and Liabilities Management	λ_i	Risk aversion	20
	m_s	Maturity of nb-securities	0.995
Short-term Interbank Loans and Bonds	γ_{vi}	Valuation elasticity of trust component	0
	γ_r	Valuation elasticity of return component	1
	γ_σ	Valuation elasticity of standard deviation component	5
	g^A	Discrimination factor in calculation of $a_{i,c,t}^I$	5
	g^I	Interbank interest rate intensity	0.1
Expectation Formation	θ^S	Error correction in calculation of $\mathrm{E}[\log(\omega_{s,t}^S)]$	0.1
	θ^Ω	Error correction in calculation of $\mathrm{E}[\log(\Omega_{c,t}^C)]$	0.01
	ψ^S	Memory parameter in calculation of $\mathrm{Var}(r_s^S)$, $\hat{\mathrm{Cov}}(r_{s1}^S, r_{s2}^S)$, $\hat{\mathrm{Cov}}(r_c^B, r^I)$, $\hat{\mathrm{Cov}}(r_s^S, r^I)$, $\hat{\mathrm{Cov}}(r_c^B, r_s^S)$	0.1
	ψ^B	Memory parameter in calculation of $\mathrm{Var}(r_c^B)$	0.01
Exogenous Agents			
Rest-of-world agent	λ_{row}	Vector of asset specific risk aversion parameters	Nb-assets 1-5: 50.000, 10.000 else
	E_{row}^{min}	Minimum equity	1000
	x^{row}	Aggressiveness factor	10
Central counterparty	x^R	Probability in calculation of haircuts and margin requirements	0.01
	r^M	Margin rate	0
	r^R	Repo rate	0
Investor deposits	m_D	Maturity of investor deposits	0.99
	α^D	Fraction of outstanding investor deposits at time of default	0.01
Lender of last resort	r^{LLR}	Marginal Lending Rate	$\frac{0.05}{250}$
Market Maker	g^{MMS}	Price impact factor nb-securities	0.1
	g^{MMB}	Price impact factor bank bonds	0.1
	x^I	Stopping limit interbank	0.1
	x^{MMS}	Stopping limit nb-securities	0.1
	x^{MMB}	Stopping limit bank bonds	0.1

Table 2.5: Benchmark simulation parameters

2.10.2 Commercial Bank Agents' Risk Management

The total value at risk of commercial bank c in period t is calculated as the sum of the values at risk of outstanding loans, prospective loans and refinancing costs:

$$VaR_t(\Delta L) = VaR_t^{out} + VaR_t^{prosp}(\Delta L) + VaR_t^{ref}(\Delta L, \Delta C) \tag{2.55}$$

with

$$VaR_t^{out} = \mathop{\mathrm{E}}_{c,t}\left[F_{out}^{-1}(x^L)\right] m_L L_{t-1}(1-\rho_{c,t}), \tag{2.56}$$

$$VaR_t^{prosp}(\Delta L) = \mathop{\mathrm{E}}_{c,t}\left[F_{prosp}^{-1}(x^L)\right] \Delta L \quad \text{and} \tag{2.57}$$

$$VaR_t^{ref}(\Delta L, \Delta C) = \mathop{\mathrm{E}}_{c,t}\left[F_{ref}^{-1}(x^L)\right] W_{c,t}(\Delta L, \Delta C). \tag{2.58}$$

F_{out}^{-1}, F_{prosp}^{-1} and F_{ref}^{-1} are the quantile functions of cumulative losses due to outstanding loans, prospective loans and refinancing costs, respectively, over T^{risk} periods. We define T^{risk} to be the period in which 99% of outstanding loans have been paid back. For the sake of simplicity, we assume perfect positive correlation between the individual risks in Eq.(2.55) by modeling the total value of risk as the unweighted sum of individual value of risks. $VaR_t(\Delta L)$ is therefore the upper bound for the true value of risk.

Agents obtain approximations of F_{out}^{-1} and F_{prosp}^{-1} by simulating n^{risk} evolutions of their loan portfolio over T^{risk} periods. In the l-th simulation by cb-agent c in period t, $\check{L}_{c,l,t+\tau}^{out} = \prod_{x=1}^{\tau}(1-\check{\rho}_{c,l,t+x}^{L_{out}})m_L^x$ is the remaining fraction of outstanding loans after τ periods, where $\check{\rho}_{c,l,t+x}^{L_{out}}$ is a draw from the known stochastic process of the default rate of outstanding loans. The corresponding cumulative loss per loan, $\Lambda_{c,l,t+T^{risk}}^{out}$, in period T^{risk} amounts to

$$\Lambda_{c,l,t+T^{risk}}^{out} = \sum_{\tau=1}^{T^{risk}} (\check{\rho}_{c,l,t+\tau}^{L_{out}} - (1-\check{\rho}_{c,l,t+\tau}^{L_{out}})\tilde{r}_{c,l,t}^{L_{out}})\check{L}_{c,l,t+\tau-1}^{out}. \tag{2.59}$$

Because loans in our model are never fully paid back we arbitrarily choose $T^{risk} = \log(0.01)/\log(m_L)$ (the period in which 99% of loans have been repaid) as the simulation length. We furthermore define $\mathcal{L}_{c,t}^{out}(l)$ as the l-th element of the ordered set of losses from the portfolio of outstanding loans after T^{risk} periods:

$$\mathcal{L}_{c,t}^{out} := \{\Lambda_{c,1,t+T^{risk}}^{out}, \Lambda_{c,2,t+T^{risk}}^{out}, ..., \Lambda_{c,n^{risk},t+T^{risk}}^{out}\}, \tag{2.60}$$

with the elements of the set ordered ascendingly, i.e. $\mathcal{L}_{c,t}^{out}(l) \leq \mathcal{L}_{c,t}^{out}(l+1)$. The estimates of the quantile functions of losses from outstanding loans (losses from prospective loans are derived analogously) at point x^L can be expressed as

$$\mathop{\mathrm{E}}_{c,t}[F_{out}^{-1}(x^L)] = \mathcal{L}_{c,t}^{out}(x^L n^{risk}) \quad \text{and} \quad \mathop{\mathrm{E}}_{c,t}[F_{prosp}^{-1}(x^L)] = \mathcal{L}_{c,t}^{prosp}(x^L n^{risk}). \tag{2.61}$$

Unlike the stochastic process generating loan defaults, wholesale refinancing costs are endogenous to our model. For the sake of simplicity, the risk management of cb-agents model wholesale refinancing costs in consecutive periods as i.i.d. normally distributed random variables. This allows us to derive the expected value $\mathrm{E}_{c,t}[r^W_{total}]$ and variance $\mathrm{Var}_{c,t}(r^W_{total})$ of the total wholesale refinancing costs of a loan portfolio analytically:

$$\underset{c,t}{\mathrm{E}}[r^W_{total}] = \sum_{\tau=0}^{\infty} m_L^{\tau} \hat{\mathrm{E}}_{c,t}[r^W, \psi^W] = \frac{\hat{\mathrm{E}}_{c,t}[r^W, \psi^W]}{1 - m_L} \tag{2.62}$$

$$\underset{c,t}{\mathrm{Var}}(r^W_{total}) = \sum_{\tau=0}^{\infty} m_L^{2\tau} \hat{\mathrm{Var}}_{c,t}(r^W, \psi^W) = \frac{\hat{\mathrm{Var}}_{c,t}(r^W, \psi^W)}{1 - m_L^2}. \tag{2.63}$$

Note that by discounting wholesale cost with the maturity parameter of loans m_L, we assume that the need for wholesale funding and the volume of outstanding loans to the real sector decrease at the same speed. This is a cautious assumption since loans are funded partly by customer deposits and equity. Given the quantile function of a normally distributed random variable, we compute

$$\underset{c,t}{\mathrm{E}}[F^{-1}_{ref}(x^L)] = \underset{c,t}{\mathrm{E}}[r^W_{total}] + \sqrt{2 \underset{c,t}{\mathrm{Var}}(r^W_{total})}\, \mathrm{inverf}(2x^L - 1), \tag{2.64}$$

with $\mathrm{inverf}(\cdot)$ being the inverse of the (Gauss) error function.

2.10.3 Commercial Bank Agents' Maturity Structure Of Wholesale Debt

The mean-variance optimization problem of Section 2.5.2 is

$$\max_{\mathbf{a}} \underset{c,t}{\mathrm{E}}[S] - 0.5\lambda_{c,t} \underset{c,t}{\mathrm{Var}}(S), \tag{2.65}$$

with

$$\underset{c,t}{\mathrm{E}}[S] = \underset{c,t}{\mathrm{E}}[r^L] - \frac{W_{c,t}}{L_{c,t}} \left(a_{c,t} \underset{c,t}{\mathrm{E}}[\bar{r}^B] + (1 - a_{c,t}) \underset{c,t}{\mathrm{E}}[\bar{r}^I]) \right) \tag{2.66}$$

$$\underset{c,t}{\mathrm{Var}}(S) = \underset{c,t}{\mathrm{Var}}(r^L) + (a_{c,t}\frac{W_{c,t}}{L_{c,t}})^2 \underset{c,t}{\mathrm{Var}}(\bar{r}^B) + ((1 - a_{c,t})\frac{W_{c,t}}{L_{c,t}})^2 \underset{c,t}{\mathrm{Var}}(\bar{r}^I) \tag{2.67}$$

$$+ \quad 2 \left(-a_{c,t}\frac{W_{c,t}}{L_{c,t}} \underset{c,t}{\mathrm{Cov}}(r^L, \bar{r}^B) - (1 - a_{c,t})\frac{W_{c,t}}{L_{c,t}} \underset{c,t}{\mathrm{Cov}}(r^L, \bar{r}^I) \right. \tag{2.68}$$

$$+ \quad \left. a_{c,t}(1 - a_{c,t})(\frac{W_{c,t}}{L_{c,t}})^2 \underset{c,t}{\mathrm{Cov}}(\bar{r}^B, \bar{r}^I) \right) \tag{2.69}$$

Differentiating Eq. (2.65) with respect to a yields

$$\frac{\partial U_{c,t}}{\partial a_{c,t}} = -\frac{W_{c,t}}{L_{c,t}} \left(\underset{c,t}{\mathrm{E}}[\bar{r}^B] - \underset{c,t}{\mathrm{E}}[\bar{r}^I] \right) - 0.5\lambda_c \left(2a_{c,t}(\frac{W_{c,t}}{L_{c,t}})^2 \underset{c,t}{\mathrm{Var}}(\bar{r}^B) - 2(1 - a_{c,t})(\frac{W_{c,t}}{L_{c,t}})^2 \underset{c,t}{\mathrm{Var}}(\bar{r}^I) \right)$$
$$-\lambda_c \left(-\frac{W_{c,t}}{L_{c,t}} \underset{c,t}{\mathrm{Cov}}(r^L, \bar{r}^B) + \frac{W_{c,t}}{L_{c,t}} \underset{c,t}{\mathrm{Cov}}(r^L, \bar{r}^I) + (1 - 2a_{c,t})(\frac{W_{c,t}}{L_{c,t}})^2 \underset{c,t}{\mathrm{Cov}}(\bar{r}^B, \bar{r}^I) \right) \tag{2.70}$$

After setting Eq. (2.70) to 0 and rearranging, one obtains

$$a^*_{c,t} = \frac{-\frac{L_{c,t}}{W_{c,t}} \frac{\mathrm{E}_{c,t}[\bar{r}^B] - \mathrm{E}_{c,t}[\bar{r}^I]}{\lambda_c} + \frac{L_{c,t}}{W_{c,t}} \left(\mathrm{Cov}_{c,t}(r^L, \bar{r}^B) - \mathrm{Cov}_{c,t}(r^L, \bar{r}^I) - \mathrm{Cov}_{c,t}(\bar{r}^B, \bar{r}^I) \right) + \mathrm{Var}_{c,t}(\bar{r}^I)}{\mathrm{Var}_{c,t}(\bar{r}^B) + \mathrm{Var}_{c,t}(\bar{r}^I) - 2\frac{L_{c,t}}{W_{c,t}} \mathrm{Cov}_{c,t}(\bar{r}^B, \bar{r}^I)} \tag{2.71}$$

Replacing $\mathrm{E}_{c,t}[\bar{r}^B]$ with $\mathrm{E}_{c,t}[m_B r^B_{c,t} + (1 - m_B) r^B_{c,t+1}] = \mathrm{E}_{c,t}[r^B]$ and setting the covariance terms to zero yields

$$a^*_{c,t} = \frac{\mathrm{Var}_{c,t}(\bar{r}^I) - \frac{L_{c,t}}{W_{c,t}} \frac{\mathrm{E}_{c,t}[r^B] - \mathrm{E}_{c,t}[\bar{r}^I]}{\lambda_c}}{\mathrm{Var}_{c,t}(\bar{r}^I) + (1 - m_B)^2 \mathrm{Var}_{c,t}(r^B)} \tag{2.72}$$

With

$$\underset{c,t}{\mathrm{E}}[r^I] = \underset{c,t}{\mathrm{E}}[r^I] = r^I_{c,t} \tag{2.73}$$

$$\underset{c,t}{\mathrm{E}}[\bar{r}^I] = (1 - \underset{c,t}{\mathrm{E}}[a^{LLR}, \psi^I])\,\underset{c,t}{\mathrm{E}}[r^I] + \underset{c,t}{\mathrm{E}}[a^{LLR}, \psi^I] r^{LLR}_t \tag{2.74}$$

$$\underset{c,t}{\mathrm{E}}[a^{LLR}_t] = \underset{c,t}{\mathrm{E}}[a^{LLR}] \tag{2.75}$$

$$\underset{c,t}{\mathrm{Var}}(x) := \hat{\mathrm{Var}}_{c,t}(x, \psi), \tag{2.76}$$

Eq. (2.72) can be rewritten as

$$a^*_{c,t} = \frac{\hat{\mathrm{Var}}_{c,t}(\bar{r}^I, \psi^I) - \frac{L_{c,t}}{W_{c,t}} \frac{\mathrm{E}_{c,t}[r^B] - \mathrm{E}_{c,t}[\bar{r}^I]}{\lambda_c}}{\hat{\mathrm{Var}}_{c,t}(\bar{r}^I, \psi^I) + (1 - m_B)^2 \hat{\mathrm{Var}}_{c,t}(r^B, \psi^B)} \tag{2.77}$$

2.10.4 Allocation Of Loans On The Overnight Interbank Market

Cb-agent c's evaluation of investment bank i's loan offer is computed as follows:

$$U^C_{c,i,t} = (v_{c,i,t})^{\gamma_v} (u_{c,i,t})^{\gamma_u}, \tag{2.78}$$

with $v_{c,i,t}$ being a measure of trust, $u_{c,i,t}$ measuring relative funding costs and γ_v and γ_u being the valuation elasticities of the respective factors. The relative attractiveness of the interbank interest rate $r^I_{i,c,t}$ demanded by ib-agent i for a loan to cb-agent c is straightforward. The closer the interest rate is to the currently lowest demanded rate $r^{low}_{c,t}$, the higher its attractiveness. We therefore define

$$u_{i,c,t} = \frac{r^{low}_{c,t}}{r^I_{i,c,t}}. \tag{2.79}$$

To compute the trust measure, we define a transaction variable

$$\xi_{i,c,t} = \begin{cases} 1 & \text{if a transaction takes place} \\ -1 & \text{if no transaction takes place} \end{cases}$$

In order to make the trust measure a function of past transaction,

$$\Xi_{c,i,t} = \begin{cases} \Xi^{max} & \text{if} \quad \Xi_{c,i,t-1} + \frac{\xi_{i,c,t-1}}{\Xi^{max}} \geq \Xi^{max} \\ \Xi^{min} & \text{if} \quad \Xi_{c,i,t-1} + \frac{\xi_{i,c,t-1}}{\Xi^{max}} \leq \Xi^{min} \\ \Xi_{c,i,t-1} + \frac{\xi_{i,c,t-1}}{\Xi^{max}} & \text{else} \end{cases}$$

is a variable of transactions aggregated over time. Within the range of permissible values, trust $v_{c,i,t} \in [\Xi^{min}/\Xi^{max}, 1]$ increases when agents engage in a transaction and decreases otherwise:

$$v_{c,i,t} = \frac{\Xi_{c,i,t}}{\Xi^{max}} \tag{2.80}$$

The parameter $\Xi^{max} > 1$ defines the stickiness with which trust increases or decreases. The larger Ξ^{max}, the more transactions are necessary before two agents completely trust each other. The relative attractiveness of the interbank interest rate $r^I_{i,c,t}$ demanded by ib-agent i for a loan to cb-agent c is straightforward. The closer the interest rate is to the currently lowest demanded rate $r^{low}_{c,t}$, the higher its attractiveness:

$$u_{i,c,t} = \frac{r^{low}_{c,t}}{r^I_{i,c,t}} \tag{2.81}$$

With both evaluation factors defined, the interbank loan commercial bank c receives from investment bank i is computed as follows:

$$I_{c,i,t} = \begin{cases} I_{i,c,t} & \text{if } I_{c,t} - I_{i,c,t} - \sum_{\iota \in \mathcal{U}} I_{\iota,c,t} \geq 0 \\ I_{c,t} - \sum_{\iota \in \mathcal{U}} I_{\iota,c,t} & \text{if } I_{i,c,t} > I_{c,t} - \sum_{\iota \in \mathcal{U}} I_{\iota,c,t} \\ 0 & \text{else} \end{cases} \tag{2.82}$$

with $I_{i,c,t}$ (note the switched order of subindices) denoting the loan volume offered by ib-agent i and $\mathcal{U} := \{\iota | U^C_{\iota,c,t} > U^C_{i,c,t}\}$ being the set of offers with a higher valuation U^C than the offer from ib-agent i.

2.10.5 Portfolio Optimization Of Investment Bank Agents

We solve the mean-variance optimization problem

$$\mathbf{a}^*_{i,t} = \arg\max_{\mathbf{a}} \mathbf{a}' \mathrm{E}_{i,t}[\mathbf{r}] - 0.5\lambda_i \mathbf{a}' \mathbf{\Sigma}_{i,t} \mathbf{a} \qquad \text{s.t.} \tag{2.83}$$

$$a^R_{i,j,t} = \begin{cases} -(1-h^R_{j,t}) a^S_{i,j,t} & \text{if } a^S_{i,j,t} \geq 0 \text{ and } h^R_{j,t} \leq h^D_t \\ 0 & \text{else} \end{cases} \tag{2.84}$$

$$a^M_{i,j,t} = \begin{cases} -(1+k_{j,t}) a^S_{i,j,t} & \text{if } a^S_{i,j,t} < 0 \\ 0 & \text{else} \end{cases} \tag{2.85}$$

$$a^D_{i,t} = -(1-h^D_{j,t})(a^I_{i,t} + a^B_{i,t} + \sum_{j \in \mathcal{D}} a^S_{i,j,t}) \tag{2.86}$$

$$\{a^I_{i,t}, a^B_{i,t}, a^C_{i,t}\} \geq 0 \quad \text{and} \quad \mathbf{a}'\mathbf{1} = 1 \tag{2.87}$$

via an iterative process. In order to save computation time, we rewrite the problem given in Eq. (2.83)-(2.87) by integrating constraints (2.84)-(2.86) into the budget constraint and adjusting expected returns by associated financing costs. The rewritten problem only features nb-securities, the two types of interbank loans and cash, reducing the size of the weight vector from $3n^S + n^C + 3$ to $n^S + n^C + 2$. We define $\hat{\mathbf{a}} = (\mathbf{a}^S, a^I, \mathbf{a}^B, a^C)'$ as the vector of asset weights and $\mathrm{E}_{i,t}[\hat{\mathbf{r}}] = (\hat{\mathbf{r}}^S_{i,t}, \hat{r}^I_{i,t}, \hat{\mathbf{r}}^B_{i,t}, r^C)'$ as the vector of adjusted returns. The individual components of the latter are

$$\hat{r}^S_{i,j,t} = \begin{cases} \mathrm{E}_{i,t}[r^S_j] - r^R_{j,t} & \text{if } (\mathrm{E}_{i,t}[r^S_j] \geq 0) \text{ and } h^R_{j,t} \leq h^D_{i,t} \\ \mathrm{E}_{i,t}[r^S_j] - r^D_{i,t} & \text{if } (\mathrm{E}_{i,t}[r^S_j] \geq 0) \text{ and } h^R_{j,t} > h^D_{i,t} \\ \mathrm{E}_{i,t}[r^S_j] - r^M_{j,t} & \text{if } (\mathrm{E}_{i,t}[r^S_j] < 0) \end{cases} \tag{2.88}$$

$$\hat{r}^I_{i,t} = \mathop{\mathrm{E}}_{i,t}[r^I] - r^D_{i,t} \tag{2.89}$$

$$\hat{r}^B_{i,c,t} = \mathop{\mathrm{E}}_{i,t}[r^B_c] - r^D_{i,t}, \tag{2.90}$$

The vector $\omega_{i,t} = (\omega^S, \omega^I, \omega^B, \omega^C)$ captures haircuts and margin requirements in the budget constraint. The individual components of $\omega_{i,t}$ are

$$\omega^S_{j,t} = \begin{cases} h^R_{j,t} & \text{if } \mathrm{E}_{i,t}[r^S_j] \geq 0 \text{ and } h^R_{j,t} \leq h^D_{i,t} \\ h^D_{i,t} & \text{if } \mathrm{E}_{i,t}[r^S_j] \geq 0 \text{ and } h^R_{j,t} > h^D_{i,t} \\ -k_{j,t} & \text{if } \mathrm{E}_{i,t}[r^S_j] < 0 \end{cases}, \tag{2.91}$$

$$\omega^I_{i,t} = h^D_{i,t} \tag{2.92}$$

$$\omega^B_{i,c,t} = h^D_{i,t} \tag{2.93}$$

$$\omega^C = 1, \tag{2.94}$$

$$\tag{2.95}$$

The problem can now be restated as

$$\mathbf{a}^*_{i,t} = \arg\max_{\mathbf{a}} \mathbf{a}'\mathrm{E}_{i,t}[\hat{\mathbf{r}}] - 0.5\lambda_i \mathbf{a}'\boldsymbol{\Sigma}_{i,t}\mathbf{a} \quad \text{s.t.} \quad \omega_{i,t}\mathbf{a} = 1. \tag{2.96}$$

The vector $\mathbf{a}^*_{i,t}$ is derived from the first order conditions in matrix form

$$\lambda_i \boldsymbol{\Sigma}\mathbf{a} + \mu\omega'_{i,t} = \hat{\mathbf{r}}_{i,t} \tag{2.97}$$

$$\omega_{i,t}\mathbf{a} = 1, \tag{2.98}$$

where μ is the Lagrange multiplier. With $\mathbf{V} := \begin{Bmatrix} \boldsymbol{\Sigma}_{i,t} & \omega'_{i,t} \\ \omega_{i,t} & 0 \end{Bmatrix}$, $\tilde{\mathbf{a}} := (\hat{\mathbf{a}}, \frac{\mu}{\lambda_i})'$ and $\mathbf{y} := (\frac{\hat{\mathbf{r}}_{i,t}}{\lambda_i}, 1)'$ and after rearranging, one obtains

$$\tilde{\mathbf{a}}^* = \mathbf{V}^{-1}\mathbf{y}. \tag{2.99}$$

The iterative process works as follows: We first solve for the weights vector $\tilde{\mathbf{a}}^*$ that maximizes the problem stated in Eq. (2.96). We then check whether the resulting weights violate any of following asset-specific conditions

$$a^S_j \geq 0 \text{ and } \mathop{\mathrm{E}}_{i,t}[r^S_j] \geq 0 \tag{2.100}$$

$$a^S_j < 0 \text{ and } \mathop{\mathrm{E}}_{i,t}[r^S_j] < 0 \tag{2.101}$$

$$a^I \geq 0 \tag{2.102}$$

$$a^B_c \geq 0 \tag{2.103}$$

$$a^C \geq 0 \tag{2.104}$$

$$\tag{2.105}$$

and set them to zero if this is the case. We repeat these two steps until the current weights vector equals that of the last iteration. Finally, to ensure optimality, we check whether the resulting vector satisfies the Kuhn-Tucker conditions.

2.10.6 Overnight Interbank Loans To Commercial Banks

The evaluation function for cb-agents is given by

$$U^I_{i,c,t} = \begin{cases} \left(\frac{v_{c,i,t}}{\max(v_{i,t})}\right)^{\gamma_{vi}} \left(\frac{\mathrm{E}_{i,t}[r^I_c]}{\max(\mathrm{E}_{i,t}[r^I_c])}\right)^{\gamma_r} \exp\left(\frac{-\sqrt{\mathrm{Var}_{i,t}(r^I_c)}}{\max(\sqrt{\mathrm{Var}_{i,t}(r^I_c)})}\right)^{\gamma_\sigma} & \text{if } \ U^I_{i,c,t} > U^{\min} \\ 0 & \text{else} \end{cases} \tag{2.106}$$

with γ_{vi}, γ_r and γ_σ being the valuation elasticities of the trust, return and standard deviation components, respectively. Since expected returns may be negative, $\gamma_r \in \mathbb{N}^{+,\text{odd}}$ must be a positive and odd natural number. To avoid that ib-agents offer very small amounts to cb-agents with a low valuation, we introduce a cut-off value $U^{\min}$.

The portfolio weight for an overnight interbank loan to commercial bank c is found via a multinomial choice model:

$$a^I_{i,c,t} = \frac{\exp\left(g^A \frac{U^I_{i,c,t}}{\max(U^I_{i,c,t})}\right)}{\sum_{c=1}^{n^C} \exp\left(g^A \frac{U^I_{i,c,t}}{\max(U^I_{i,c,t})}\right)}. \tag{2.107}$$

The parameter $g^A \geq 0$ thereby determines how strongly ib-agents discriminate between the valuations of different cb-agents. When $g^A = 0$ interbank loans are distributed equally to commercial banks regardless of their valuation, while $g^A = \infty$ implies that only the agent with the highest valuation will be offered interbank loans.

2.10.7 Supply Of Investor Deposits

Starting from the law of motion for equity under the stress scenario, one arrives at a representation for $E_{i,t+\tau}$ that is dependent on the initial values for equity and deposits and the parameters $\rho^D_{i,t}$ and m_D:

$$\begin{aligned}
E_{i,t+1} &= (1+\rho^D_{i,t})E_{i,t} + \rho^D_{i,t}D_{i,t} && (2.108)\\
E_{t+2} &= (1+\rho^D_{i,t})E_{i,t+1} + \rho^D_{i,t}D_{i,t+1} && (2.109)\\
&= (1+\rho^D_{i,t})((1+\rho^D_{i,t})E_{i,t} + \rho^D_{i,t}D_{i,t}) + \rho^D_{i,t}m_D D_{i,t} && (2.110)\\
&= (1+\rho^D_{i,t})^2 E_{i,t} + (1+\rho^D_{i,t})\rho^D_{i,t}D_{i,t} + \rho^D_{i,t}m_D D_{i,t} && (2.111)\\
E_{t+3} &= (1+\rho^D_{i,t})((1+\rho^D_{i,t})^2 E_{i,t} + (1+\rho^D_{i,t})\rho^D_{i,t}D_{i,t} + \rho^D_{i,t}m_D D_{i,t}) + \rho^D_{i,t}m_D^2 D_{i,t} && (2.112)\\
&= (1+\rho^D_{i,t})^3 E_{i,t} + (1+\rho^D_{i,t})^2\rho^D_{i,t}D_{i,t} + (1+\rho^D_{i,t})\rho^D_{i,t}m_D D_{i,t} + \rho^D_{i,t}m_D^2 D_{i,t} && (2.113)\\
&\ldots && (2.114)\\
E_{i,t+\tau} &= (1+\rho^D_{i,t})^\tau E_{i,t} + \rho^D_{i,t}D_{i,t}\sum_{x=0}^{\tau-1}(m_D)^x(1+\rho^D_{i,t})^{\tau-1-x} && (2.115)\\
&= (1+\rho^D_{i,t})^\tau E_{i,t} + \rho^D_{i,t}D_{i,t}(1+\rho^D_{i,t})^{\tau-1}\sum_{x=0}^{\tau-1}\left(\frac{m_D}{1+\rho^D_{i,t}}\right)^x && (2.116)
\end{aligned}$$

Given that $\frac{m_D}{1+\rho^D_{i,t}} \neq 1$, the geometric series in Eq. (2.116) can be rewritten and we obtain

$$E_{i,t+\tau} = (1+\rho^D_{i,t})^\tau E_{i,t} + \rho^D_{i,t}D_{i,t}(1+\rho^D_{i,t})^{\tau-1}\left(\frac{1-\left(\frac{m_D}{1+\rho^D_{i,t}}\right)^\tau}{1-\left(\frac{m_D}{1+\rho^D_{i,t}}\right)}\right). \tag{2.117}$$

If $\frac{m_D}{1+\rho^D_{i,t}} = 1$, Eq. (2.116) can be rewritten as

$$E_{i,t+\tau} = (1+\rho^D_{i,t})^\tau E_{i,t} + \rho^D_{i,t}D_{i,t}(1+\rho^D_{i,t})^{\tau-1}\tau \tag{2.118}$$

By replacing τ with T^{def}, setting $E_{i,t+T^{def}} = 0$ and rearranging, one arrives at the solution

$$D^*_{i,t} = \begin{cases} \dfrac{-(1+\rho^D_{i,t})E_t}{\rho^D_{i,t}\left(\dfrac{1-\left(\frac{m_D}{1+\rho^D_{i,t}}\right)^{T^{def}}}{1-\left(\frac{m_D}{1+\rho^D_{i,t}}\right)}\right)} & \text{if } \frac{m_D}{1+\rho^D_{i,t}} \neq 1 \\ \dfrac{-(1+\rho^D_{i,t})E_t}{\rho^D_{i,t}T^{Def}} & \text{if } \frac{m_D}{1+\rho^D_{i,t}} = 1 \end{cases} \tag{2.119}$$

2.10.8 Modeling The Liquidity Coverage Ratio

Commercial Banks

Outflows for commercial bank c in period t under the stress scenario defined in the LCR regulation are calculated as

$$\text{outflows}_{c,t} = w^D D_{c,t} + w^I I_{c,t}(1+\bar{r}^I_{c,t}) + w^B B_{c,t}\sum_{\tau=1}^{30} m_B^{\tau-1}(\bar{r}^B_{c,t} + 1 - m_B). \tag{2.120}$$

The run-off rates for customer deposits, bonds and overnight interbank debt are defined by the regulator as $w^D = 0.03$, $w^B = 1$ and $w^I = 1$, respectively.[40] Equation 2.120 can be rewritten in terms of the share of long-term wholesale debt, $a_{c,t}$:

$$\begin{aligned} \text{outflows}_{c,t} =& w^D D_{c,t} + W_{c,t}(1-a_{c,t})\underbrace{w^I(1+\bar{r}^I_{c,t})}_{c0_{c,t}} + \underbrace{w^B B_{c,t-1} m_B \frac{1-m_B^{30}}{1-m_B}(\bar{r}^B_{c,t-1} - r^B_{c,t})}_{c1_{c,t}} \\ &+ W_{c,t}a_{c,t}\underbrace{w^B\left(\frac{1-m_B^{30}}{1-m_B}(r^B_{c,t}+1-m_B)\right)}_{c2_{c,t}}. \end{aligned} \tag{2.121}$$

Inflows are calculated as

$$\text{inflows}_{c,t} = \underbrace{w^L\sum_{\tau=1}^{30} m_L^{\tau-1}(1-\mathop{\mathrm{E}}_{c,t}[\rho^L])^{\tau}(\tilde{r}^L_{c,t}+1-m_L)}_{c3_{c,t}} L_{c,t} \tag{2.122}$$

Using Equations 2.120 and 2.122, Equation 2.51 can be rewritten as

$$W_{c,t} = \begin{cases} \frac{L_{c,t}-E_{c,t}-D_{c,t}(1-0.25w_D)+0.25c1_{c,t}}{1-0.25((a_{c,t}\cdot c2_{c,t})+(1-a_{c,t})c0_{c,t})} & \text{if inflows} > 0.75 \text{ outflows} \\ \frac{L_{c,t}(1-c3_{c,t})-E_{c,t}-D_{c,t}(1-w_D)+c1_{c,t}}{1-((a_{c,t}\cdot c2_{c,t})+(1-a_{c,t})c0_{c,t})} & \text{if inflows} \leq 0.75 \text{ outflows} \end{cases} \tag{2.123}$$

Investment Banks

As described in Section 2.7.2, ib-agents comply with the LCR by ensuring that every investment is LCR-neutral, i.e. sufficient HQLA are accumulated to cover

[40] The parameters are taken from Basel III (2013)

the outflows associated with the financing of the investment. For an investment in nb-securities, Eq. 2.52 takes the form

$$\underbrace{\alpha^R_{i,s,t} w^R_s (1-h^R_{s,t}) + (1-\alpha^R_{i,s,t})(1-h^D_{i,t}) \sum_{\tau=1}^{30} m_D^{\tau-1}(r^D_{i,t}+1-m_D)}_{\text{expected outflow of one unit of nb-security } s \text{ under stress}} = \underbrace{(1-\alpha^R_{i,s,t}) w^S_s}_{\text{HQLA}}, \tag{2.124}$$

where $\alpha^R_{i,s,t}$ is the share of repo funding of investment bank i of nb-security s in period t. Rearranging gives the optimal share

$$\alpha^R_{i,s,t} = \frac{w^S_s - (1-h^D_{i,t})c4_{i,t}}{w^R_s(1-h^R_{s,t}) + w^S_s - (1-h^D_{i,t})c4_{i,t}} \quad \text{with} \quad c4_{i,t} = \sum_{\tau=1}^{30} m_D^{\tau-1}(r^D_{i,t}+1-m_D). \tag{2.125}$$

For an investment in bank bonds, Eq. 2.52 takes the form

$$\underbrace{x^B_{i,c,t} a^B_{i,c,t}(1-h^D_{i,t})c4_{i,t}}_{\text{outflow}} - \underbrace{a^B_{i,c,t} c5_{i,c,t}}_{\text{inflow}} = \underbrace{x^B_{i,c,t} a^B_{i,c,t}(1-h^D_{i,t}) - a^B_{i,c,t}(1-h^D_{i,t})}_{\text{cash}} \tag{2.126}$$

$$\text{with} \quad c5_{i,c,t} = \sum_{\tau=1}^{30} (1 - \mathop{\mathrm{E}}_{i,t}[\Omega^C_c])^\tau m_B^{\tau-1} \frac{B_{c,t}}{P^B_{c,t} Q^B_{c,t}} (\bar{r}^B_{i,c,t} + 1 - m_B).$$

As the LCR regulation requires banks to hold at least 25% of their outflows in HQLA, the amount of investor deposits required per bank bond, $x^B_{i,c,t}$, has a lower bound $x^{Bmin}_{i,c,t}$ that satisfies

$$0.25 \underbrace{x^{Bmin}_{i,c,t} a^B_{i,c,t}(1-h^D_{i,t})c4_{i,t}}_{\text{outflow}} = \underbrace{x^{Bmin}_{i,c,t} a^B_{i,c,t}(1-h^D_{i,t}) - a^B_{i,c,t}(1-h^D_{i,t})}_{\text{cash}}. \tag{2.127}$$

The amount of investor deposits required per bank bond purchased, $x^B_{i,c,t}$, is then given by

$$x^B_{i,c,t} = \max \left\{ \frac{c5_{i,c,t} - (1-h^D_{i,t})}{(1-h^D_{i,t})(c4_{i,t}-1)}, \underbrace{\frac{1}{1-0.25c4_{i,t}}}_{x^{Bmin}_{i,c,t}} \right\}. \tag{2.128}$$

Analogously, the amount of investor deposits required per overnight interbank loan, $x^I_{i,t}$, is derived from

$$\underbrace{x^I_{i,t} a^I_{i,t}(1-h^D_{i,t})c4_{i,t}}_{\text{outflow}} - \underbrace{a^I_{i,t} \sum_{c=1}^{n^I} a^I_{i,c,t} c6_{i,c,t}}_{\text{inflow}} = \underbrace{x^I_{i,t} a^I_{i,t}(1-h^D_{i,t}) - a^I_{i,t}(1-h^D_{i,t})}_{\text{cash}} \quad \text{and} \tag{2.129}$$

$$0.25 \underbrace{x^{Imin}_{i,t} a^I_{i,t}(1-h^D_{i,t})c4_{i,t}}_{\text{outflow}} = \underbrace{x^{Imin}_{i,t} a^I_{i,t}(1-h^D_{i,t}) - a^I_{i,t}(1-h^D_{i,t})}_{\text{cash}}, \tag{2.130}$$

resulting in

$$x_{i,t}^{I} = \max\left\{\frac{\sum_{c=1}^{n^I} a_{i,c,t}^{I}(1-\mathrm{E}_{i,t}[\Omega_c^C])(1+r_{i,c,t}^{I})-(1-h_{i,t}^{D})}{(1-h_{i,t}^{D})(c4_{i,t}-1)}, \underbrace{\frac{1}{1-0.25c4_{i,t}}}_{x_{i,t}^{Imin}}\right\}. \tag{2.131}$$

Chapter 3

Bank Manager Sentiment, Loan Growth And Bank Risk

3.1 Introduction

The financial crisis of 2007–2009 has sparked a renewed interest in the underlying drivers of credit booms and busts. New evidence from novel datasets that span multiple countries over long periods of time suggests that bank credit growth is a strong predictor of financial crisis (Schularick and Taylor, 2012; Aikman et al., 2014) and poor bank performance (Foos et al., 2010; Baron and Xiong, 2017; Fahlenbrach et al., 2017). A prominent rational explanation for why credit growth is associated with financial fragility is the existence of dynamic financial frictions (see e.g. Benanke and Gertler, 1989; Kiyotaki and Moore, 1997; Gertler and Kiyotaki, 2010). In these models, financial frictions imply that exogenous shocks to firms' net worth become amplified and are highly persistent, which in turn affects the firms' ability to access external funding (Brunnermeier et al., 2012). While a large positive shock can initiate a series of periods with increasing net worths and leverage, i.e. a credit boom, a large negative shock can have the opposite effect, i.e. causing a credit bust.[1] In contrast, more recent contributions argue that credit cycles can be traced back to behavioral factors (e.g. Greenwood and Hanson, 2013; Greenwood et al., 2016; López-Salido et al., 2017; Bordalo et al., 2018). In line with Minsky (1977) and Kindleberger (1978), this strand of the literature takes the view that a credit crisis arises when banks and bank investors suddenly realize that their expectations of economic fundamentals have been too high and adjust their expectations accordingly. Consistent with this view, Greenwood and Hanson (2013), Baron and Xiong (2017) and Fahlenbrach et al. (2017) present empirical evidence for the prevalence of systematic over-optimism on the part of banks, equity analysts and investors in equities and corporate bonds.

Against this background, the aim of this paper is to provide evidence on how

[1] The predictions of these models motivate the empirical analysis of the relationship between financial crisis and preceding rapid buildups of leverage (López-Salido et al., 2017).

systematic over-optimism on the part of banks may affect the amount of credit that they supply to the real sector. For this purpose, I proceed in three steps. First, given that survey data on the expectations of bank managers is unavailable to me, I extract a measure of the sentiment of bank managers from bank earnings press release documents using methods from textual analysis. My use of the textual sentiment of earnings press release documents is motivated by the finding from the accounting literature that managers use corporate disclosures to signal their expectations about future firm outcomes (see e.g. Li, 2010; Davis et al., 2012). The resulting textual sentiment score is available for medium-sized and large European banks on the banking group level for the period between the first quarter of 2006 and the second quarter of 2019.

To verify the validity of the textual sentiment score, I study its distribution over time and its relationship with important bank-specific and macroeconomic variables. The results of these analyses strongly suggest that the textual sentiment scores contain information about the fundamentals of banks, i.e. their performance, business models and the economic environments in which they operate. More specifically, over the sample period, the textual sentiment score is on average positively associated with GDP growth rates and interbank interest rates and negatively associated with bank-level impairments on loans, the term spread and the OIS spread. Furthermore, I find that banks that rely more on retail deposits and that are less reliant on interest income show higher levels of textual sentiment on average. Since I am interested in the incremental informational content of the earnings press release documents, I remove the influence of the bank-specific and macroeconomic variables from the textual sentiment score and define the resulting variable as the bank manager sentiment index.[2]

Second, I explore whether the bank manager sentiment index has an extrapolative structure, i.e. whether it is associated with past realizations of economic fundamentals.[3] Expectations with an extrapolative structure imply over-optimism: if expectations depend on past realizations of economic fundamentals, the logical implication is that expectations will not be fully in line with current fundamentals. Thus, relative to current fundamentals, expectations will be too high, i.e. excessively optimistic, or too low, i.e. excessively pessimistic (Greenwood et al., 2016).[4] When forming their expectations, bank managers might, for example, extrapolate recent news on impairments in their loan portfolios (see e.g. Greenwood et al., 2016) or on macroeconomic developments (see e.g. Bordalo et al., 2018) into the future. In my empirical investigation, I find two pieces of evidence that suggest that the bank managers' expectations are partially backward looking. First, I document that GDP growth rates have incremental predictive power for future values of the bank manager sentiment index. Second, I find that the bank manager sentiment index is auto-correlated, implying that innovations in variables that were found to be correlated with the bank manager sentiment index are also associated with its subsequent realizations.

[2]The name is inspired by the manager sentiment index of Jiang et al. (2019).

[3]The existence of extrapolative expectation formation rules is well documented in the finance literature. Extrapolative expectations are, for example, prevalent in survey data on stock return expectations (Greenwood and Shleifer, 2014), survey data on the expectations of CFOs with respect to macroeconomic developments and the future profitability of their own firms (Gennaioli et al., 2016) and forecasts of credit spreads (Bordalo et al., 2018).

[4]The implicit assumption here is that only the current state of the economy matters for decision making, which is a widely used assumption in economics and finance.

Third, I study whether the bank manager sentiment index is associated with the investment decisions of banks and their equity investors. On the part of banks, I explore whether the bank manager sentiment index has incremental predictive power for loan growth. I do this for two reasons. First, evidence of a relationship between the two variables strengthens my case that the bank manager sentiment index reflects information about the expectations of bank managers. Second, a positive relationship between bank manager sentiment and loan growth is a necessary condition for the existence of a link between excessively optimistic expectations of bank managers and high loan growth rates. In my empirical analysis, I find that the bank manager sentiment index has incremental but weak predictive power for loan growth over the subsequent six months. When I replace the bank manager sentiment by its components, I find that the predictive power of the bank manager sentiment index is mainly driven by the share of negative words that managers use in their press releases.

On the part of bank equity investors, I explore whether the sentiment of bank managers influences how bank investors perceive the risk associated with loan growth. The perceived riskiness of a bank is an important determinant of its cost of capital, which in turn is an important determinant of the bank's investments in loans. Motivated by empirical evidence suggesting that equity market participants sometimes seem to be too optimistic when judging the risk associated with high bank loan growth (see e.g. Baron and Xiong, 2017; Fahlenbrach et al., 2017), I hypothesize that the bank manager sentiment index is associated with the risk associated with bank loan growth and that the perceived risk associated with loan growth is lower when bank managers are more optimistic.[5] Using *SRISK* (Brownlees and Engle, 2016) as my measure for the risk perception of market participants, I find that the association between loan growth and risk decreases in the bank manager sentiment index. Put differently, the higher the sentiment of a bank's managers, the lower is the coefficient on loan growth in a regression of systemic risk. However, the empirical model implies that the relationship between loan growth and risk is only negative if the bank manager sentiment index is relatively high, i.e. more than two of its standard deviations higher than its unconditional average.

The paper proceeds as follows. Section 3.2 summarizes the related literature and explains how this paper extends the respective strands of research. Section 3.3 introduces the textual sentiment score and other variables used throughout the paper. Section 3.4 studies the development of textual sentiment scores over time, their relationships with important bank-specific and macroeconomic variables and defines the bank manager sentiment index. Section 3.5 explores whether bank manager sentiment is extrapolative in past fundamentals. Sections 3.6.1 examines whether the bank manager sentiment index is predictive for subsequent loan growth rates. Section 3.6.2 studies whether the perception risk associated with bank loan growth by bank equity investors differs when bank managers are optimistic versus when they are pessimistic. Finally, Section 3.7 summarizes and discusses the results.

[5] Baron and Xiong (2017) find that rapid credit expansions on the country level predict low and sometimes negative aggregate bank equity returns, suggesting that investors sometimes underestimate the risk associated with bank loan growth. Fahlenbrach et al. (2017) show that equity analysts' forecasts of profitability and growth for high loan growth banks are often too optimistic and are subsequently revised downwards.

3.2 Literature Overview

My paper contributes to three strands of research. First, it is related to the literature that links credit cycles to behavioral factors, which was initiated by Minsky (1977). In this literature, a positive association between credit growth and financial fragility is explained by overly optimistic or extrapolative expectations. Recent theoretical contributions to this literature are Greenwood et al. (2016) and Bordalo et al. (2018). Greenwood et al. (2016) present a model in which lenders extrapolate past realizations of credit defaults. The extrapolative expectation formation rules imply that credit cycles in the model are more persistent than the cycles in the underlying fundamentals. Bordalo et al. (2018) present a model in which credit cycles are driven by what they label diagnostic expectations of agents. Under the assumption of diagnostic expectations, agents assign too high probabilities to future outcomes that become more likely relative to the observed current state. Diagnostic expectations imply that agents have extrapolative expectations and neglect risk. In contrast to the model of Greenwood et al. (2016), the model of Bordalo et al. (2018) predicts that a crisis can be triggered by changing expectations without a corresponding decrease in fundamentals.

Empirical evidence for excessive optimism in credit markets is presented in Greenwood and Hanson (2013), Greenwood et al. (2016), López-Salido et al. (2017), Fahlenbrach et al. (2017) and Bordalo et al. (2018). Greenwood and Hanson (2013) study the relationship between the average credit quality of new corporate bond issues and excess corporate bond returns. They find that lower average debt issuer quality predicts low excess corporate bond returns, where the latter also turn negative. One explanation for this relationship given by Greenwood and Hanson (2013) is that corporate bond investors over-extrapolate past low corporate bond default rates, causing them to demand risk premia that are too low. By showing that measures of sentiment in the credit market depend on past realization of defaults, Greenwood et al. (2016) provide additional empirical evidence for extrapolative expectations in credit markets. López-Salido et al. (2017) use the expected excess return for bearing credit risk as a proxy of credit market sentiment and present evidence that high credit market sentiment predicts low real GDP growth and a decrease of net debt issuance relative to net equity issuance. Fahlenbrach et al. (2017) present bank-level evidence that is consistent with excessively optimistic bank managers and equity analysts. They show that high loan growth banks do not provision more for loan losses than low loan growth banks and that equity analysts expect that high loan growth banks have higher future loan and earnings growth rates relative to low loan growth banks. Lastly, Bordalo et al. (2018) document that analysts expect credit spreads to be more persistent than they actually are and that analysts' forecast revisions are negatively associated with past credit spreads.

Second, my paper contributes to the empirical literature concerned with the relationship between credit growth and bank stability. Country-level evidence (e.g. Schularick and Taylor, 2012; Aikman et al., 2014; Baron and Xiong, 2017) as well as firm-level evidence (e.g. Foos et al., 2010; Fahlenbrach et al., 2017) suggest that high bank loan growth is positively associated with financial fragility and negatively associated with subsequent bank performance. Schularick and Taylor (2012) introduce a new dataset that covers 12 developed countries over the period 1870–2008. The evidence from this dataset suggests that the occurrence of a financial crisis is more likely if there has been a credit boom in the preceding five years (Schularick and Taylor, 2012), that the severity of recessions increased in the build-up of bank credit during the preceding boom (Jordà et al., 2013) and that credit booms predict the occurrence of banking crisis (Aikman et al., 2014). Deploying a different panel dataset which covers 20 developed countries over the period 1920–2012, Baron and Xiong (2017) document that large increases in bank lending predict an increase in bank equity crash risk and that holders of bank equity have not been compensated for this crash risk in terms of higher bank equity returns. On the bank level, Foos et al. (2010) Fahlenbrach et al. (2017) find that high loan growth predicts high subsequent loan loss provisions and lower returns on assets. Moreover, Fahlenbrach et al. (2017) show that high loan growth banks significantly underperform low loan growth banks in terms of their stock market returns.

Third, my paper contributes to the growing finance and accounting literature that studies the informational content of the textual sentiment of voluntary corporate disclosures. Within this literature, researchers study different text sources (e.g. annual reports, press releases, conference call transcripts), use different approaches to classify the content of these text sources (e.g. dictionary-based approaches, machine learning) and use different ways to calculate an aggregate sentiment score from the classified text contents (Kearney and Liu, 2014). Overall, the empirical evidence suggests that the textual sentiment of corporate disclosures contains incremental informational content about the future performance of the reporting firms and that market participants respond to textual sentiment. For example, Li (2010) applies a machine-learning approach to the forward-looking statements in the Management Discussion and Analysis section of 10-K and 10-Q filings to study the incremental predictive power of textual sentiment for future earnings. He finds that textual sentiment is positively correlated with future return on assets up to three quarters ahead. Loughran and McDonald (2011) demonstrate that general dictionaries wrongly classify many words as negative that do not have a negative connotation in a financial context and introduce new word lists that are better suited to capture the textual sentiment in financial texts. They find that the proportion of negative words, as identified by their new word list, is negatively associated with 10-K filing returns. Davis et al. (2012) study a large sample of earnings press release documents published between 1998 and 2003. They find that textual sentiment is a predictor of future returns on assets and that the unexpected portion of their measure has incremental and positive predictive power for cumulative abnormal returns over a three day window centered around the earnings press release date. Huang et al. (2013) study earnings press releases published between 1997 and 2007 and present evidence for strategic firm behavior. They find that textual sentiment is more positive if firms have strong incentives to bias investor expectations upward and that higher sentiment is associated with a larger stock price response to the announcement. They also find that the initial increases in stock prices are accompanied with subsequent return reversals. Gandhi et al. (2019) specifically look at annual reports of US banks and find that the proportion of negative words is positively related to different measures of financial distress. Jiang et al. (2019) construct an aggregate manager sentiment index from firm-level textual sentiment. They find that aggregate manager sentiment is negatively associated with stock returns on the market level and in the cross-section and that it has predictive power for aggregate investment. My paper is the closest related to the strand of the literature that uses a dictionary-based approach to classify words as positive or negative and calculates sentiment by subtracting the share of positive words by the share of negative words (also called net sentiment), i.e. Davis et al. (2012), Huang et al. (2013) and Jiang et al. (2019). Using a new sample of European banks, I extend the literature by showing that textual sentiment of earnings press release documents is associated with the investment decisions of banks and their equity investors.

3.3 Data

This section introduces the textual sentiment and bank sentiment variables, as well as bank-specific and macroeconomic control variables used in my analyses.

3.3.1 Textual Sentiment

My measure of bank manager sentiment is based on the textual sentiment of bank earnings press release documents. My textual sentiment sample comprises all English language press releases of banks from developed European markets that are available in the database of data provider S&P Global Market Intelligence (SNL, hereafter).[6] Bank earnings press releases in the SNL database are available starting from the first quarter of the year 2005. My textual sentiment sample ends in the second quarter of the year 2019.

It takes three steps to transform earnings press release documents into final textual sentiment scores. The first step is to calculate textual sentiment scores for all earnings press release documents. To process the documents, I use the bag-of-words approach, i.e. for each document, I create a list of all words contained in the document and count how often they appear.[7] Based on the document-specific word lists, I then classify the words as having a positive connotation, having a negative connotation, or as neutral. The classification is done via the financial dictionary of Loughran and McDonald (2011). As demonstrated by Loughran and McDonald (2011), their financial dictionary is more appropriate for financial texts than standard dictionaries like the widely used Harvard Dictionary. Finally, I follow Davis et al. (2012), Huang et al. (2013) and Jiang et al. (2019) and calculate the textual sentiment score, $sent_{i,p,d}$, of the earnings press release document d of bank i for the reporting period p as the difference between the share of words that have a positive connotation, $pos_{i,p,d}$, and the share of words that have a negative connotation, $neg_{i,p,d}$, i.e.

$$sent_{i,p,d} = pos_{i,p,d} - neg_{i,p,d}, \quad \text{with} \quad pos_{i,p,d} = \frac{N^{pos}_{i,p,d}}{N_{i,p,d}} \quad \text{and} \quad neg_{i,p,d} = \frac{N^{neg}_{i,p,d}}{N_{i,p,d}}. \tag{3.1}$$

The variables $N^{pos}_{i,t,d}$, $N^{neg}_{i,t,d}$ and $N_{i,t,d}$ count the occurrences of words with a positive connotation, the occurrences of words with negative connotation and the total number of words in document d, respectively. The reporting period p thereby refers to a quarter. If the bank's reporting frequency is semi-annually,

[6]The Developed Europe category in the S&P Global Market Intelligence database comprises Austria, Belgium, Cyprus, Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom.

[7]See e.g. Gentzkow et al. (2019) for a description of the bag-of-words approach.

press textual sentiment scores are only available for the second and fourth quarter of any year.

The second step is to deal with the existence of multiple, possibly differing earnings press release documents from the same bank and for the same reporting period. For simplicity, I solve this issue by combining all textual sentiment scores by calculating the average, i.e.

$$S_{i,p} = D_{i,p}^{-1} \sum_{d=1}^{D_{i,p}} S_{i,p,d}, \tag{3.2}$$

where S refers to *sent*, *pos* or *neg* and $D_{i,p}$ is the number of earnings press release documents released by bank i at the end of reporting period p.

The third and final step is to align the frequency of all bank-level textual sentiment score time-series. About one third of the banks in the textual sentiment sample report their earnings on a semi-annual frequency, the remaining banks in the sample report quarterly. I therefore transform all time-series with a quarterly frequency into time-series with a semi-annual frequency. As in the second step, I combine the textual sentiment scores of banks with a quarterly reporting frequency by calculating a simple average, i.e. $S_{i,t} = 0.5(S_{i,p1} + S_{i,p2})$, where t refers to the first or second half of a given year (e.g. 2006H1), S refers to *sent*, *pos* or *neg* and $p1$ and $p2$ refer to the first and second quarter, respectively, within t. A detailed analysis of the final textual sentiment scores is presented in Section 3.4.

My approach to extract textual sentiment scores from earnings press release documents has two weaknesses, which are currently not addressed because they would require sophisticated technical solutions. The first weakness relates to the bag-of-word approach, which I use because of its simplicity. Since the bag-of-word approach abstracts from the contexts of a document's words, I may falsely classify words that are preceded by a negation. For example, I would falsely classify the words "good" in "not good" and "bad" in "not bad" as positive and negative, respectively. Unfortunately, I have no estimate of how prevalent the use of negations in bank earnings press release documents is and have therefore no knowledge about the direction of respective possible bias. The second weakness is that I am currently not able to determine to which reporting period a specific part of an earnings press release document relates to. As the main purpose of the document is to inform about the performance of the bank during the last reporting period, I treat the whole document as if it relates only to reporting period that ends at time t. However, earnings press release documents usually also contain forward looking passages and might also contain passages that relate to previous reporting periods. If the latter is the case, the document's textual sentiment score will be correlated with past fundamentals, which could be a problem for my analysis in Section 3.5. More specifically, my result that the GDP growth rate has incremental predictive power for subsequent realizations of bank manager sentiment could be partially or fully driven by occurrences of passages relating to past reporting periods. Section 4.8 outlines how these weaknesses could be addressed in order to increase the robustness of my results.

3.3.2 Accounting Data

I merge the textual sentiment dataset with a dataset containing semi-annual accounting data of European banks from SNL.[8] To ensure that the accounting data aligns with the content of the press releases documents, I download all variables as they have been originally reported at the end of the respective reporting period. However, if the originally reported values are not available, I use restated accounting values, i.e. accounting values that were changed retrospectively by the bank. The accounting data is available for the reporting periods 2006H1 to 2019H2. Some banks only report key balance sheet variables at the end of the fiscal year. To avoid losing those interim observations in my empirical analysis, I impute these missing values with the average of the value reported at the end of the previous year and the value reported in the same year. The dummy variable *imputed*, that indicates whether the value of at least one variable was imputed, is included in all regressions. Table 3.1 gives an overview over the accounting variables used in this paper.

Table 3.2 reports summary statistics for the intersection of the textual sentiment dataset and the accounting dataset as well as for the banks, for which no textual sentiment scores are available. The summary statistics provided in columns 2–7 of Panel A of Table 3.2 show a considerable variation in the size of the banks in the intersection of the two datasets. My sample includes both very small (the fifth percentile is 1.17 billion) and also very large banks (the ninth decile is 1,275.13 billion), as measured by their total assets (*ta*).[9] The average bank has assets of 228.26 billion, invests the majority of its assets in loans (*loans*), funds about half of its balance sheet via deposits (*deposits*) and is highly reliant on interest income (*intinc*)[10]. With an average of 2.32% and a standard deviation of 13.06%, semi-annual loan growth rates (*loangrowth*) have been on average positive but extremely volatile. The relatively high standard deviation statistic of *loangrowth* indicates the presence of outliers. An inspection of the distribution of *loangrowth* over the sample period depicted in Figure 3.1 confirms this. To limit the effect that these outliers have on my regression results, I winsorize *loangrowth* by replacing its values below the 5th percentile by the its 5th percentile and values above the 95th percentile by its 95th percentile. The percentiles are thereby calculated from the distribution of *loangrowth* specific to period t, i.e. only the distribution of *loangrowth* observed in period t is used to winsorize the observations from period t. I choose the 5th and the 95th percentiles because these quantiles are both very stable over the sample period and have a sensible magnitude. Finally, bank profitability has been particularly weak during the sample period, which includes the financial crisis of 2007–2009 and the European debt crisis of 2010–2012. On average, operating income (*opinc*) was barely sufficient to cover operating expenses (*opexp*) and impairments on loans and securities (*impair*).

Columns 8–13 in Panel A of Table 3.2 reveal that banks that release earnings press release documents systematically differ from banks that do not. The former are on average larger, invest less in loans and are therefore less reliant

[8] Accounting data with a semi-annual frequency is readily available in SNL. No transformations were necessary on my side.

[9] In my analysis, I only use the log of *ta*, which I refer to as *logta*.

[10] I have winsorized the variable *intinc* so that it lies between 0 and 1. Trading losses, which are a component of net operating income, can lead to values below 0 or above 1, which I set to 0 and 1, respectively.

Table 3.1: List of macroeconomic and financial covariates

Variable	Abbreviation	Source	Comments
Total assets	*ta*	SNL	SNL Code: 132264
Net loans to total assets	*loans*	SNL	SNL Codes: 132214 (loans), 132264 (total assets)
Cash to total assets	*cash*	SNL	SNL Codes: 246025 (cash), 132264 (total assets)
Total securities to total assets	*secs*	SNL	SNL Codes: 132191 (cash), 132264 (total assets)
Deposits to total assets	*deposits*	SNL	SNL Codes: 132288 (deposits), 132264 (total assets)
Equity to total assets	*equity*	SNL	SNL Codes: 132385 (equity), 132264 (total assets)
Total debt	*debt*	SNL	SNL Codes: 132319 (total debt), 132264 (total assets)
Operating income to total assets	*opinc*	SNL	SNL Codes: 225155 (operating income), 132264 (total assets)
Net interest income to net operating income	*intinc*	SNL	SNL Codes: 132553 (net interest income), 225155 (operating income)
Operating expenses to total assets	*opexp*	SNL	SNL Codes: 225159 (operating expenses), 132264 (total assets)
Total impairments to total assets	*impair*	SNL	SNL Codes: 225181 (impairments), 132264 (total assets)
Loan loss reserves to total assets	*reserves*	SNL	SNL Codes: 248860
GDP growth	*gdp*	Eikon Datastream	nominal, seasonally adjusted
Consumer price inflation	*infl*	Eikon Datastream	–
Three month interbank rate	*interbank*	Eikon Datastream	EURIBOR for Eurozone countries, country-specific LIBOR rates for non-Eurozone countries
Term spread	*term*	Eikon Datastream	yield on benchmark 10-year government bonds - 3-month interbank rates
OIS spread	*ois*	Eikon Datastream	3-month interbank rates - OIS rates
Market capitalization	W	Eikon Datastream	–
Bank stock returns	R_i	Eikon Datastream	total return
Market return	R_m	Eikon Datastream	Return on the MSCI Europe Index

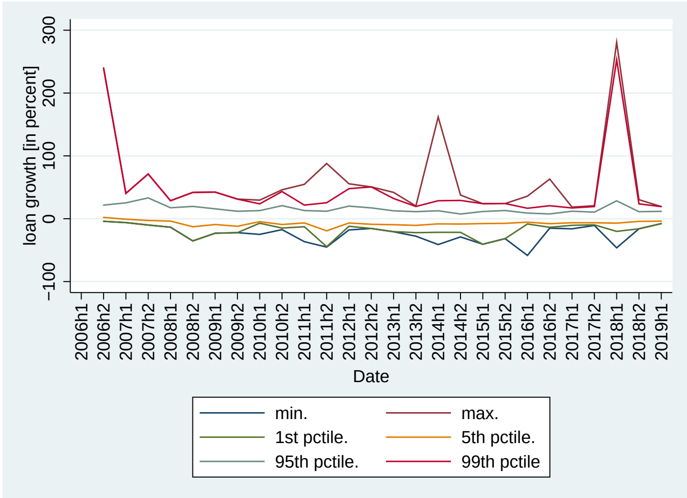
Table 3.2: Summary statistics

Panel A: Bank-level variables	Textual sentiment sample						No textual sentiment available						
Variable	N	mean	std	p5	p50	p95	N	mean	std	p5	p50	p95	$\Delta mean$
Balance sheet and income variables													
ta (in billion Euros)	3,033	228.26	428.94	1.45	45.33	1275.13	3,922	48.06	155.43	0.37	10.71	176.67	180.20***
loans (in %)	3,022	59.38	18.21	23.71	62.03	84.17	3,896	65.22	20.11	19.44	69.80	87.40	-5.84***
cash (in %)	3,027	4.45	5.59	0.09	2.35	15.391	3,841	5.41	9.54	0.13	1.92	18.71	-0.97*
secs (in %)	3,006	22.29	14.15	4.93	19.33	51.40	3,867	17.70	13.48	1.24	14.88	40.73	4.59***
deposits (in%)	3,021	51.16	19.39	18.55	51.84	81.96	3,892	50.72	24.16	0.00	55.95	82.27	0.44
equity (in %)	3,031	7.05	3.89	2.60	6.46	14.08	3,908	6 8.53	6.15	2.12	7.71	16.47	-1.47***
intinc (in %)	3,033	60.54	21.96	21.14	60.42	100.00	3,922	66.44	21.10	27.03	67.58	100.00	-5.90***
loangrowth (in %)	2,792	2.32	13.06	-7.82	1.39	15.19	3,393	2.63	16.79	-8.22	1.65	13.47	-0.31
Profitability variables													
opinc (in %)	3,016	1.33	0.88	0.34	1.23	2.64	3,815	1.45	1.44	0.15	1.19	3.21	-0.12
opexp (in %)	3,020	0.85	0.55	0.21	0.76	1.71	3,812	0.92	1.20	0.07	0.70	2.06	-0.07
impair (in %)	3,006	0.30	0.75	-0.02	0.11	1.15	3,839	0.27	0.67	-0.04	0.11	1.04	0.02

Panel B: Macro-level variables	Textual sentiment sample						No textual sentiment available						
Variable	N	mean	std	p5	p50	p95	N	mean	std	p5	p50	p95	$\Delta mean$
gdp (in %)	3,033	1.22	1.92	-2.08	1.33	3.77	3,886	1.28	1.93	-2.04	1.39	3.82	-0,06
infl (in %)	3,033	0.71	0.80	-0.40	0.61	2.08	3,886	0.75	0.79	-0.39	0.65	2.21	-0.04
interbank (in %)	3,033	1.07	1.65	-0.33	0.53	4.67	3,886	1.05	1.61	-0.50	0.52	4.67	0.02
term (in %)	3,031	1.71	2.22	-0.46	1.18	4.96	3,884	1.30	1.66	-0.37	0.92	4.08	0.40***
ois (in %)	2,852	0.26	0.30	0.02	0.14	0.76	3,753	0.27	0.30	0.01	0.20	0.84	-0.01

Note: This table presents summary statistics for the bank-specfic and macroeconomic variables used throughout this paper. The summary statistics are reported for two samples. The summary statistics for the research sample, i.e. banks, for which textual sentiment is available, are reported in columns 2–7. Columns 8–13 report the summary statistics for European banks, for which no textual sentiment scores are available. Column 14 reports the differences in means between both samples, as well as whether the differences are statistically significant at the 10%(*), 5%(**) or 1%(***) level, respectively. The statistical tests are based on standard errors clustered on the bank level.

Figure 3.1: The distribution of loan growth rates over the sample period



on interest income and have lower equity ratios (see also column 14). My results thus may not necessarily generalize to all European banks. However, since the banks in my textual sentiment sample account for a large majority of outstanding loans, my results may nevertheless contribute to our understanding of aggregate credit cycles.

3.3.3 Macroeconomic Data

I merge macro-level variables downloaded from Refinitiv Datastream and the website of the European Central Bank to the dataset containing the textual sentiment scores and accounting data. All macro-level variables are country-specific and relate to the same reporting period as the textual sentiment score and the accounting data.[11] The macro-level variables are GDP growth (nominal, seasonally adjusted; *gdp*), the consumer price inflation rate (*infl*), the three month interbank rate (*interbank*), the OIS swap rate (*ois*) and the term spread (*term*) (see Table 3.1). The variables *gdp* and *infl* have publication lags of between 1 and 2 months, i.e. the values of their realizations for period t become only known in the first half of period $t + 1$. However, I do not account for publication lags in my main analyses, because I consider these variables as proxies for the economic conditions observed by bank managers during period t.[12] All interest rate variables are semi-annual averages calculated from daily data. The OIS spread is a proxy for the degree of counterparty risk in the interbank market and is calculated as the difference between the three month

[11] Given that earnings press release documents and the accounting data are published 1–2 months after the end of a reporting period, at the time of the release, bank managers already have partial information about the macroeconomic environment during the next period. The textual sentiment score for period t might thus also be related to the realizations of macroeconomic variables between the end of t and the release of the press release document. An additional measure to increase the robustness of my results would be to also include these values in my empirical analyses.

[12] Not accounting for publication lags does not seem to pose a problem. Robustness checks (not shown), in which I account for these publication lags, yield very similar results.

interbank rate and the three month OIS swap rate (see e.g. Gorton and Metrick, 2012b). The term spread is the difference between the ten years government bond yield and the three months interbank rate and proxies for the slope of the yield curve. Given that my sample contains the periods of the the European Sovereign Debt Crisis, *term* also captures stress in sovereign debt markets.

Panel B of Table 3.2 provides summary statistics for these variables. The sample period includes both boom periods and recessions, as well as periods with very low, even negative interest rates. As column 14 reveals, *term* is on average higher in my research sample than in the sample, for which textual sentiment scores are not available. This is the result of an over-representation of banks from countries that were affected by the sovereign debt crisis in my textual sentiment sample.

3.3.4 Systemic Risk

For the listed banks in my sample, I calculate the systemic risk measure *SRISK* introduced in Brownlees and Engle (2016). *SRISK* is the dependent variable in Section 3.6.2. It is the conditional expectation of the capital shortfall of the bank under a systemic event. The capital shortfall is defined as the difference between required market equity, e.g. due to microprudential regulations, and actual market equity. The systemic event is defined as a multi-period return of the total equity market that is smaller than a threshold value c. The formular for *SRISK* (Brownlees and Engle, 2016, p. 52) is

$$SRISK_{i,t} = W_{i,t}\left[kLVG_{i,t} + (1-k)LRMES_{i,t} - 1\right], \qquad (3.3)$$

where $W_{i,t}$, $LVG_{i,t}$ and $LRMES_{i,t}$ are the market value of equity, the market leverage ratio (market equity plus the book value of debt (*debt*, hereafter) over market equity) and the the Long Run Marginal Expected Shortfall (LRMES), respectively, of bank i in period t. While $W_{i,t}$ and $LRMES_{i,t}$ can in principal be observed daily on the stock market, $LVG_{i,t}$ depends on *debt*, which can only be observed quarterly or semi-annualy.[13] Since the frequency chosen in this paper is semi-annual, $SRISK_{i,t}$ also has a semi-annual frequency. Given that the accounting data used in this study either relates to the six months ending in June or December of a given year, I use market values from the end of June and December, respectively, for all variables that are based on market prices, i.e. $W_{i,t}$ and $LRMES_{i,t}$. LRMES is defined as (Brownlees and Engle, 2016, p. 53)

$$LRMES_{i,t} = -E_t\left(R_{i,t+1:t+h} | R_{m,t+1:t+h} < c\right). \qquad (3.4)$$

The variables $R_{i,t+1:t+h}$ and $R_{m,t+1:t+h}$ are the multi-period returns of bank i and the stock market, respectively, where the parameter h defines the horizon over which the returns are calculated. To obtain $W_{i,t}$ and $LVG_{i,t}$, I download market values from Datastream and *debt* from SNL. I use Datastream to obtain bank stock returns and the return on the stock market, which are the inputs to the calculation of the LRMES. As a proxy for the European stock market, I use the MSCI Europe Index.

To calculate the LRMES of a bank, I assume that its stock return and that of the market are generated by a bivariate normal distribution with mean zero. The

[13]Due to the publication lag of *debt*, the realization of $LVG_{i,t}$ becomes known only after the end of period t. I implicitly assume that the market participants can forecast *debt*.

bivariate normal model has the advantage that it has an (approximate) closed-form solution (Brownlees and Engle, 2016). The parameters to be estimated are the standard deviation of the market return ($\sigma_{m,t}$), the standard deviation of the stock return of the bank ($\sigma_{i,t}$) and their coefficient of correlation ($\rho_{i,t}$). Given $\sigma_{i,t}$, $\sigma_{m,t}$ and $\rho_{i,t}$, the LRMES of bank i at time t can be approximated by (Brownlees and Engle, 2016, p. 55)

$$LRMES_{i,t} \approx \sqrt{h}\rho_{i,t}\sigma_{i,t}\frac{\phi(\frac{c}{\sigma_{m,t}})}{\Phi(\frac{c}{\sigma_{m,t}})}, \tag{3.5}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the normal distributions' density and the distribution function, respectively. Since these values are likely to be dynamic, I estimate $\sigma_{i,t}$, $\sigma_{m,t}$ and $\rho_{i,t}$ with a rolling window of 60 months of stock return data, i.e. each parameter is estimated with the monthly returns between $t-59$ and t. With regard to the parameters h and c, I adopt the values chosen by Brownlees and Engle (2016) and set them to 1 month and 10%, respectively. I set the parameter k to 3%, which corresponds to the current Basel III leverage ratio requirement. Since it is measured in Euros, I scale *SRISK* by the enterprise value of the bank, i.e. I divide it by the sum of its market equity and the book value of its debt ($W_{i,t} + debt_{i,t}$).[14]

Figure 3.2 depicts the distribution of scaled *SRISK* over the sample period. *SRISK* has been negative on average in the large majority of periods, meaning that the banks in my sample had capital surpluses on average. Periods with particular high levels of risk have been the second half of 2008 (the global financial crisis), the first half of 2012 (the European sovereign debt crisis) and the first half of 2016 (the Brexit referendum). In the cross-section, the dispersion between banks remains relatively stable over time. While the 25% most risky banks had a conditional expected capital shortfall in the majority of periods, the 25% least risky banks had conditional expected capital surpluses. With the exception of the year 2012, median *SRISK* has been negative over the sample period.

3.4 The Properties of Textual And Bank Manager Sentiment Scores

The aim of this section is to verify the validity of my textual sentiment scores. I first study the developments of the textual sentiment scores and the shares of positive and negative words, respectively, over time. I then explore the relationship between the three textual sentiment variables and important bank-specific and macroeconomic variables. In the last step, I describe how I construct the bank manager sentiment index from textual sentiment scores.

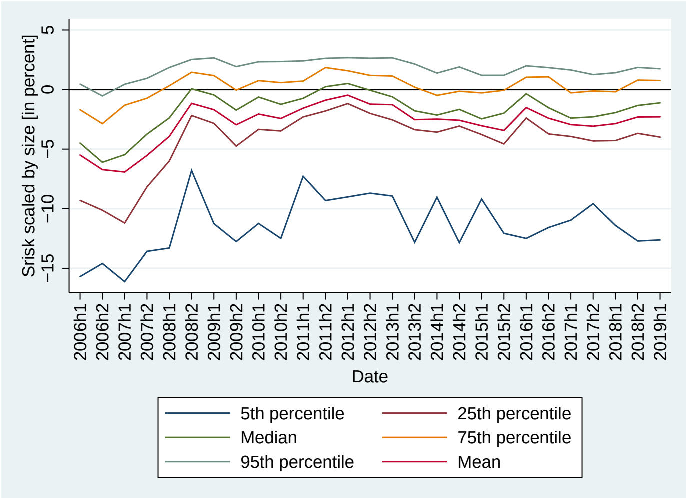
3.4.1 Textual Sentiment Scores Over Time

Figure 3.3a depicts the textual sentiment score over the sample period.

Consistent with global events, the average of *sent* is negative in the crisis years 2008 and 2009 (i.e. during the global financial crisis) and 2011 to 2013 (i.e.

[14] I scale by enterprise value and not by the size of the balance sheet, because *SRISK* is based on market equity.

Figure 3.2: The distribution of SRISK over the sample period

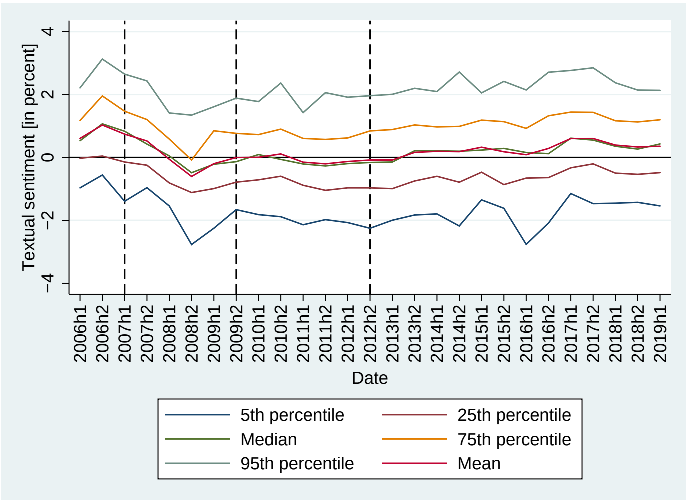


during the European sovereign debt crisis) and positive in boom periods, i.e. before the year 2008 and after the year 2013. Average *sent* starts to decrease in 2007, remains around zero between the end of 2009 and 2013 and recovers afterwards. Figure 3.3b reveals that the decrease in average *sent* before the financial crisis is predominantly driven by an increase in the average of *neg*. While the average of *neg* doubles between 2007H1 and 2008H2 (from 0.98% to 1.99%), the average of *pos* only decreases by about 19.17% (from 1.71% to 1.39%). The upward trend in the average of *sent*, which has its start in the year 2013, is driven by opposing trends in *pos* and *neg*.

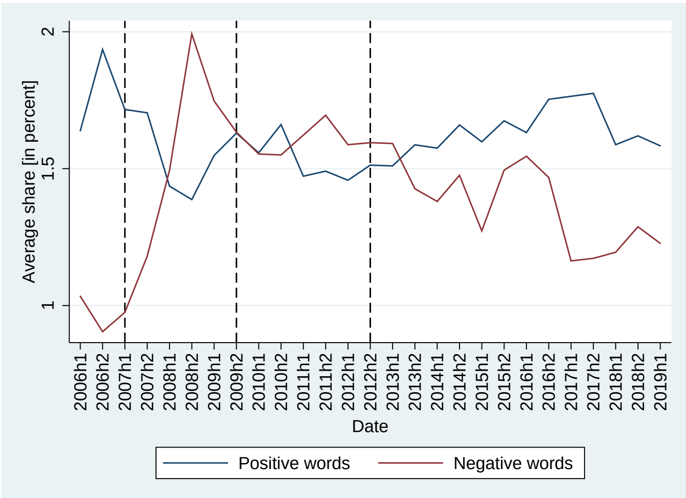
3.4.2 Textual Sentiment Scores On The Bank Level

To shed some light on the informational content of the textual sentiment scores, I run separate regressions of *sent*, *pos* and *neg* on a set of bank characteristics, macroeconomic state variables, country fixed effects and bank fixed effects. The bank-specific and country-specific variables come from three categories: profitability measures, bank business model indicators and macroeconomic state variables. The profitability variables are *opinc*, *opexp* and *impair*. Given that textual sentiment scores are extracted from earnings press release documents, I expect that the profitability variables are directly related to *sent*. The business model indicators include *loans*, *deposits*, *equity*, *intinc* and the logarithm of *ta*. The motivation for the inclusion of the business model proxy variables is that some bank business models may have been more successful than others since 2006, which I expect to be reflected in *sent*. Finally, the set of country-specific macroeconomic state variables encompasses *gdp*, *infl*, *interbank*, *term* and *ois*. Since a more favorable macroeconomic environment, i.e. high values of *gdp* and *term* and low values of *ois*, is positive for the business of banks, I expect the first two variables to be positively associated with *sent* and *ois* to be negatively associated with *sent*.

Figure 3.3: Textual sentiment



(a) The distribution of the textual sentiment score over time



(b) The averages of *pos* and *neg*

Note: These figures plot properties of the distributions of *sent* (Figure 3.3a), *pos* and *neg* (Figure 3.3b) over the sample period. The vertical lines indicate the start of the global financial crisis, the end of the global financial crisis and the end of the European sovereign debt crisis, respectively.

Country-specific And Bank-specific Differences In Textual Sentiment Scores

Differences in culture and communication styles across countries and banks may have a significant impact on textual sentiment scores. Under the assumption that these differences are constant over time, I first attempt to quantify the incremental explanatory power of country and bank fixed effects. Adjusted R^2 statistics from separate regressions of *sent*, *pos* and *neg* on profitability, business model, macroeconomic, country dummy and bank dummy variables are documented in Table 3.3. The first column reports the results from my baseline regression model, which only includes the profitability, business model and macroeconomic variables. The adjusted R^2 statistics range from 8.50% for *pos* to 18.50% for *neg*. The majority of the variation in the textual sentiment score and its components thus remains unaccounted for. Next, I include country dummy variables to measure the incremental explanatory power of country fixed effects. The second column of Table 3.3 reveals that country fixed effects have sizable explanatory power for the three textual sentiment variables. With an increase of approximately 138%, *pos* sees the highest relative increase, suggesting that country-specific factors are an especially important determinant of the occurrence of words with a positive connotation in earnings press release documents. Finally, I replace the country dummy variables by bank dummy variables, which produces the highest increases in adjusted R^2. As the third column of Table 3.3 shows, bank fixed effects account for over 50% of the variation in the dependent variables. The incremental explanatory power of bank fixed effects relative to the baseline specifications ranges from 35.40 to 42.40 percentage points. These results indicate that bank fixed effects are the most important determinant of *sent*, *pos* and *neg*. They also highlight the necessity to control for bank fixed effects in the following investigations.

Table 3.3: Country-specific and bank-specific differences in textual sentiment scores

	(1)	(2)	(3)
Adjusted R^2 (in %)	I (baseline)	II	III
sent	16.80	29.70	55.70
pos	8.50	20.20	51.10
neg	18.50	31.80	53.90

Note: This table reports adjusted R^2 statistics from separate regressions of *sent*, *pos* and *neg* on bank-specific and country-specific macroeconomic variables, country fixed effects and bank fixed effects. The baseline model (I) only includes the profitability, business model and macroeconomic variabes. The second model (II) is augmented by country fixed effects. In the third model (III), country fixed effects are replaced by bank fixed effects.

The Textual Sentiment Score, Bank Characteristics And The Macroeconomic Environment

Next, I study the relationships between the three textual sentiment variables and the profitability, business model and macroeconomic state variables in detail.

The empirical model is

$$S_{i,t} = \mathbf{X}_{i,t}^{profit}\boldsymbol{\beta}^{profit} + \mathbf{X}_{i,t}^{bm}\boldsymbol{\beta}^{bm} + \mathbf{X}_{c,t}^{macro}\boldsymbol{\beta}^{macro} + u_i + v_h + \epsilon_{i,t}, \tag{3.6}$$

where i indexes banks, t indexes time (e.g. 2006H1), c indexes countries and h indicates whether t relates to the first or second half of the year. The variable $S_{i,t}$ refers to $sent_{i,t}$, $pos_{i,t}$ or $neg_{i,t}$ of bank i in period t. The vectors $\mathbf{X}_{i,t}^{profit}$, $\mathbf{X}_{i,t}^{bm}$ and $\mathbf{X}_{i,t}^{macro}$ hold the profitability, business model and macroeconomic variables, respectively. I further include bank fixed effects u_i and season dummies (i.e. half-year fixed effects) v_h to control for time-invariant unobservables specific to each bank and to seasonal effects, respectively.[15]

The regression results are reported in Table 3.4. Somewhat surprisingly, *impair* is the only profitability variable in the regression on *sent* that is statistically different from zero (column 1). On average, higher impairments are associated with a decrease in *pos* (column 2), an increase in *neg* (column 3) and consequently a decrease in *sent*. While the variable *opinc* has only a positive and statistically significant relationship with *pos*, the variable *opexp* is statistically insignificant in all three regressions.

Of the business model variables, *deposits*, *equity* and *intinc* are statistically significant at the 5% level. A more stable funding structure, i.e. higher ratios of deposits and equity to total assets, is on average associated with higher levels of *sent*. In terms of economic significance, *deposits* is the most important variable in the regression. Lastly, a larger dependence on interest income is associated with lower bank manager sentiment on average, whereby larger values of *intinc* coincide with lower values of *pos* and higher values of *neg* on average.

Of the macroeconomic variables, all variables with exception of *infl* are statistically significant at the 5% level. While *gdp* and *interbank* are on average positively associated with *sent*, the variables *term* and *ois* are on average negatively associated with *sent*. All four variables are thereby only associated with *neg*. The negative coefficient on *termspread* is unexpected, given that banks typically engage in maturity transformation, which is more profitable when the spread between long-term and short-term rates is larger. However, since the European sovereign debt crisis falls within the sample period, *term* might also measure sovereign risk, which I expect to be negatively associated with textual sentiment.

The Bank Manager Sentiment Index

In the previous section, I have shown that the textual sentiment score and its components are related to variables that capture important bank characteristics and the macroeconomic environment in which the banks operate. I have also shown that bank fixed effects, which are likely to capture time-invariant aspects of the banks' culture and communication styles, are the most important determinant of textual sentiment. Together, these variables explain about 60% of the variation in textual sentiment. The high overlap between the textual sentiment score and these variables indicates that the textual sentiment score is a valid indicator of the sentiment of bank managers.

[15] Time and country-time fixed effects are not included because they would absorb a large fraction of the variation in bank-specific and macroeconomic variables.

Table 3.4: Textual sentiment, bank characteristics and the macroeconomic environment.

	(1) $sent_t$	(2) pos_t	(3) neg_t
$impair_t$	-0.12***	-0.07***	0.11***
	(0.02)	(0.02)	(0.03)
$opinc_t$	0.10*	0.09**	-0.06
	(0.06)	(0.04)	(0.05)
$opexp_t$	-0.02	0.02	0.05
	(0.06)	(0.06)	(0.05)
$logta_t$	0.29	0.23	-0.21
	(0.26)	(0.28)	(0.23)
$loans_t$	0.05	-0.07	-0.15**
	(0.07)	(0.07)	(0.08)
$deposits_t$	0.22**	0.22***	-0.12
	(0.09)	(0.08)	(0.09)
$equity_t$	0.10**	0.05	-0.10**
	(0.05)	(0.04)	(0.05)
$intinc_t$	-0.12***	-0.07**	0.12***
	(0.03)	(0.03)	(0.03)
gdp_t	0.07***	0.02	-0.09***
	(0.02)	(0.02)	(0.02)
$infl_t$	-0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)
$interbank_t$	0.13***	0.04	-0.17***
	(0.04)	(0.04)	(0.04)
$term_t$	-0.08**	-0.02	0.10***
	(0.03)	(0.03)	(0.04)
ois_t	-0.14***	-0.02	0.19***
	(0.02)	(0.02)	(0.03)
$imputed$	0.05	0.06	-0.01
	(0.06)	(0.06)	(0.06)
Constant	0.98***	0.58***	-0.93***
	(0.10)	(0.10)	(0.10)
Bank fixed effects	Yes	Yes	Yes
Season fixed effects	Yes	Yes	Yes
N	2,805	2,805	2,805
R^2	0.59	0.55	0.58
Adj. R^2	0.56	0.51	0.54

Note: This table documents the results of separate regressions of *sent*, *pos* and *neg* on bank-specific and macroeconomic variables. All variables are standardized. The variable *imputed* indicates whether missing values for an observation have been estimated via interpolation. The standard errors are clustered on the bank level and are reported in parenthesis. Bank fixed effects are included as dummy variables. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

I assume that the non-overlapping part of the textual sentiment score, i.e. the remaining 40% of the variance that remains unaccounted for, reflects information about the sentiment of bank managers. I therefore define a new sentiment variable, the bank manager sentiment index, which are the residuals from the regression of the textual sentiment score on the profitability variables, business model variables, macroeconomic variables, seasonal (half-year) fixed effects and bank fixed effects:[16]

$$sent^*_{i,t} = sent_{i,t} - (\mathbf{X}^{profit}_{i,t}\hat{\boldsymbol{\beta}}^{profit} + \mathbf{X}^{bm}_{i,t}\hat{\boldsymbol{\beta}}^{bm} + \mathbf{X}^{macro}_{c,t}\hat{\boldsymbol{\beta}}^{macro} + \hat{u}_i + \hat{v}_h). \quad (3.7)$$

The components of the textual sentiment score pos and neg are orthogonalized accordingly, resulting in the variables pos^* and neg^*.

3.4.3 Summary

The results of the analyses carried out in this chapter strongly suggest that the bank manager sentiment index captures relevant information about the fundamentals of the bank. The development of the bank manager sentiment over the sample period is consistent with global events. Moreover, the bank manager sentiment index and its components co-vary with important profitability, business model and macroeconomic variables, whereas the directions of these relationships are, with the exception of the term spread, as expected.

3.5 Do Bank Managers Extrapolate Past Fundamentals?

In this section, I explore whether the bank manager sentiment index has an extrapolative structure, i.e. whether it is associated with past realizations of the bank-specific and macroeconomic variables. I therefore estimate the model

$$S^*_{i,t} = \alpha + \beta_1 S^*_{i,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\beta}_2 + X^{bm}_{i,t-1}\boldsymbol{\beta}_3 + v_h + u_i + \epsilon_{i,t}, \quad (3.8)$$

where the variable $S^*_{i,t}$ represents either $sent^*_{i,t}$, $pos^*_{i,t}$ or $neg^*_{i,t}$, respectively. The vector $\boldsymbol{\beta}_2$ holds the coefficients on the variables of interest, which are the bank-specific and macroeconomic state variables, $\mathbf{X} = \left(X^{profit}_{i,t}, X^{macro}_{i,t}\right)$, lagged by one month. To isolate the effect of past fundamentals on sentiment, I control for lagged business model variables, $X^{bm}_{i,t}$ and lagged bank sentiment variables, $S^*_{i,t-1}$, whereas the lagged sentiment variables are not included in all specifications. Finally, I include bank fixed effects u_i and seasonal dummies v_h to control for unobserved time-invariant bank heterogeneity and seasonal effects, respectively.

[16] With this definition of the bank manager sentiment index, I treat the relationships between textual sentiment scores and bank-specific and macroeconomic fundamentals as linear and time-invariant. This assumption might be inappropriate, for example because the relationships between textual sentiment scores and bank-specific and macroeconomic fundamentals might be dependent on whether the macro-economy is booming or in a recession period or whether a bank has financial problems or not. If this is the case, the bank manager sentiment index will still contain information about fundamentals. However, the relatively low number of sample periods constitute a problem for the estimation of more complex, non-linear models of textual sentiment. I therefore do not consider more complex models.

Table 3.5 documents the regression results. I begin by estimating Equation (3.8) without controlling for the auto-correlation inherent in the sentiment variables, i.e. I drop $S^*_{i,t-1}$. The results of these regressions are shown in columns 1 to 3. These columns reveal that there is a statistically significant relationship between lagged *gdp* and $sent^*$ (column 1), as well as both components of the latter (columns 2 and 3). One standard deviation increase in lagged *gdp* is associated with average increase in $sent^*$ of approximately 0.10 standard deviations. While lagged *gdp* is positively associated with *pos*, it is negatively associated with neg^*.

Next, I estimate Equation (3.8), i.e. I do not drop the lagged textual sentiment variables. Columns 4 to 6 of Table 3.5 document the regression results. The coefficients on the lagged textual sentiment variables all are positive and statistically significant at the 5% level. With respect to *gdp*, controlling for lagged sentiment has virtually no impact on its coefficients and standard errors in the regressions of $sent^*$, pos^* and neg^*. In contrast to the specifications in which the first lags of the dependent variables are not included (columns 1–3), the coefficient on lagged *ois* is statistically significant at the 5% level in column 4. As the result in column 4 suggests, a one standard deviation increase in lagged *ois* is on average associated with an increase in $sent^*$ of 0.07 standard deviations. The result that bank managers seem to extrapolate past realizations of *gdp* remains valid when I use the Arellano–Bover/Blundell–Bond system estimator to estimate Equation (3.8) (columns 7–9 of Table 3.5).[17] The results documented in columns 7–9 also suggest that lagged *ois* is not associated with either $sent^*$, pos^* or neg^*, which contradicts the results obtained by the OLS estimator.

In summary, the evidence reported in Table 3.5 is consistent with the hypothesis that bank managers extrapolate economic fundamentals into the future. Past realizations of *gdp* have incremental predictive power for subsequent realizations of the bank manager sentiment index. Furthermore, the results suggest that the bank manager sentiment index is auto-correlated, implying that innovations in variables that were found to be correlated with $sent^*$ are also associated with subsequent realizations of $sent^*$.

3.6 Bank Manager Sentiment And The Investment Decisions Of Banks and Their Investors

In this section, I study whether the bank manager sentiment index is associated with the investment decisions of banks and their equity investors. In Section 3.6.1, I explore whether the bank manager sentiment index has incremental predictive power for the bank's loan growth over the subsequent six months. In Section 3.6.2, I study whether the sentiment of bank managers influences how bank investors perceive the risk associated with loan growth.

[17] The Arellano–Bover/Blundell–Bond system estimator produces consistent estimates of the coefficients of interest in a dynamic panel setting (Arellano and Bond, 1991; Blundell and Bond, 1998). In a dynamic panel setting, a bias may arise because the first lag of the dependent variable and the error term are correlated (see e.g. Baltagi, 2008). Although this bias decreases with the number of periods (Nickell, 1981), Judson and Owen (1999) show that it can be still quiet large when the panel length is as large as 30.

Table 3.5: Is bank manager sentiment extrapolative in economic fundamentals?

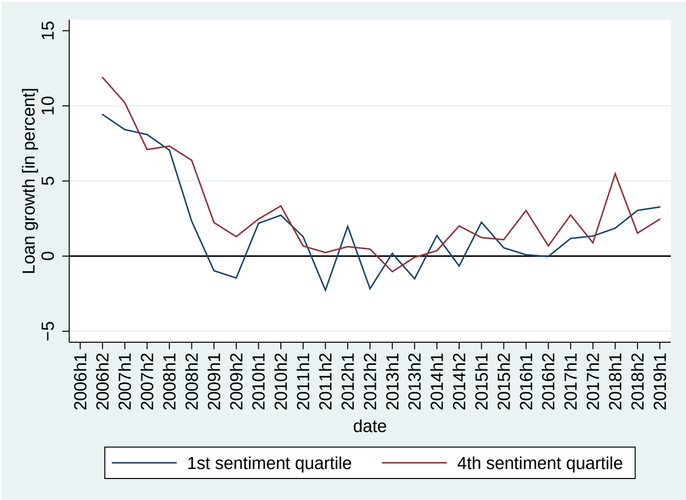
	(1) $sent_t^*$	(2) pos_t^*	(3) neg_t^*	(4) $sent_t^*$	(5) pos_t^*	(6) neg_t^*	(7) $sent_t^*$	(8) pos_t^*	(9) neg_t^*
$impair_{t-1}$	-0.04	-0.03	0.02	-0.04	-0.03	0.02	-0.02	-0.04	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.04)
$opinc_{t-1}$	-0.00	-0.01	-0.01	0.00	-0.01	-0.01	-0.11	-0.05	-0.01
	(0.05)	(0.06)	(0.04)	(0.04)	(0.05)	(0.04)	(0.10)	(0.04)	(0.05)
$opexp_{t-1}$	-0.01	0.03	0.04	-0.00	0.03	0.03	0.06	0.08	0.15
	(0.12)	(0.11)	(0.08)	(0.10)	(0.10)	(0.07)	(0.16)	(0.15)	(0.13)
gdp_{t-1}	0.10***	0.07**	-0.08***	0.11***	0.08**	-0.09***	0.12***	0.10***	-0.09***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$interbank_{t-1}$	0.01	0.01	-0.01	0.00	0.01	0.00	0.11	0.06	-0.09
	(0.08)	(0.06)	(0.08)	(0.07)	(0.06)	(0.06)	(0.09)	(0.07)	(0.11)
$term_{t-1}$	0.07	0.05	-0.06	0.07*	0.05	-0.05	0.12*	0.11*	-0.01
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)	(0.07)	(0.06)
ois_{t-1}	0.07*	0.06*	-0.04	0.07**	0.07*	-0.04	0.04	0.06	-0.01
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)
$sent_{t-1}^*$				0.23***			0.09**		
				(0.04)			(0.05)		
pos_{t-1}^*					0.14***			-0.03	
					(0.04)			(0.05)	
neg_{t-1}^*						0.26***			0.17***
						(0.04)			(0.03)
Constant	-0.00	-0.03	-0.03	-0.01	-0.03	-0.02	-0.00	-0.03	-0.00
	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.05)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,138	2,138	2,138	2,138	2,138	2,138	2,138	2,138	2,138
R^2	0.01	0.00	0.01	0.06	0.02	0.08	NA	NA	NA
Adjusted R^2	0.00	-0.02	0.00	0.06	0.02	0.07	NA	NA	NA

Note: This table documents the results of separate regressions of $sent^*$, pos^* and neg^* on lagged bank-specific and macroeconomic variables. All specifications include the lagged version of the business model variables specified Section 3.4.2 as control variables. All specifications also include the variable *imputed*, which indicates whether missing values for an observation have been estimated via interpolation. All variables are standardized. Specifications 1–3 and 4–6 are estimated with the fixed effects estimator. The standard errors are clustered on the bank level and are reported in parenthesis. Specifications 7–9 are estimated with the Arellano–Bover/Blundell–Bond system estimator with robust standard errors. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

3.6.1 Is Bank Manager Sentiment Predictive For Loan Growth?

A first look at the average loan growth rates of the most optimistic and the most pessimistic banks depicted in Figure 3.4 suggests that the bank manager sentiment index is positively associated with loan growth rates.[18]

Figure 3.4: Average loan growth rates for high sentiment and low sentiment banks



Note: This figure compares the development of loan growth rates for high sentiment banks and low sentiment banks. It has been constructed as follows: every six months, banks have been sorted into quartiles based on the bank manager sentiment index. The depicted loan growth rates are then calculated as the average of the seasonally-adjusted growth rates over the next six months within the quartiles. Loan growth rates are winsorized at the 5th and 95th percentile.

To test whether there is indeed a difference between the loan growth rates of the two groups, I run regressions of loan growth rates on $sent^*$ and control variables. Therefore, I estimate variants of the following models

$$loan\ growth_{i,t+1} = \alpha + \beta_1 sent^*_{i,t} + \mathbf{X}_{i,t}\gamma + u_i + v_t + w_{c,t} + \epsilon_{i,t}, \tag{3.9}$$

$$loan\ growth_{i,t+1} = \alpha + \beta_1 pos^*_{i,t} + \beta_2 neg^*_{i,t} + \mathbf{X}_{i,t-1}\gamma + u_i + v_t + w_{c,t} + \epsilon_{i,t}, \tag{3.10}$$

where $loan\ growth_{i,t+1}$ is the one-period ahead loan growth rate and $\mathbf{X}_{i,t}$ is a vector holding the control variables *cash*, *secs* and *reserves*. The variables u_i, v_t and $w_{c,t}$ capture bank, time and country-time fixed effects, respectively. All variables are standardized, which enables a better assessment of economic significance.

The regression results documented in the first column of Table 3.6 suggest that the bank manager sentiment index on its own is predictive of subsequent

[18]The figure has been constructed as follows: every six months, banks have been sorted into quartiles based on bank manager sentiment. The loan growth rates depicted in Figure 3.4 are then calculated as the average of the seasonal-adjusted growth rates over the next six months within the quartiles.

loan growth, but has only very weak predictive power. While the coefficient on *sent** is statistically significant at the 1% level, the variation in *sent** accounts only for about 0.6% of the variation in loan growth rates, adjusted for the number of variables in the model. A one standard deviation increase in *sent** is associated with an average increase in the loan growth rate of 0.07 standard deviations. As column 2 Table 3.6 reveals, the association between *loangrowth* and lagged *sent** is mainly driven by *neg**. Whereas the coefficient on *neg** has a similar magnitude as that on *sent** in column 1, while *pos** appears to be not associated with loan growth. Interestingly, the combination of *pos** and *neg** accounts for a larger fraction of the variance of *loangrowth* than *sent**.

As robustness tests, I include additional control variables and estimate models (3.9) and (3.10) with time and country-time fixed effects. When I include the control variables *cash*, *secs* and *reserves* into the model, I find that the coefficients on *sent** and *neg** (columns 3 and 4 of Table 3.6) are somewhat smaller in magnitude than those from the model without those variables (columns 1 and 2), but remain highly statistically significant. The introduction of time and country-time fixed effects further reduces the coefficients on *sent** and *neg**, the former being only statistically significant at the 10% level as a result (column 5). Another difference is that the coefficient on *pos** in column 6 of Table has a negative sign.

In summary, my empirical results suggest that *sent** has weak predictive power for subsequent loan growth. Its predictive power derives from *neg**. The use of *pos** and *neg** for the purpose of predicting loan growth promises a superior prediction accuracy than *sent**.

3.6.2 Bank Manager Sentiment And The Risk Associated With Loan Growth

In the previous section, I have studied the informational content of the bank manager sentiment index for the purpose of explaining bank behavior, i.e. lending decisions. Now, I turn to the question of whether the sentiment of bank managers as measured by the bank manager sentiment index spills over to their equity investors. As has been shown empirically, equity investors and analysts are sometimes too optimistic when assessing the risk–return profile of high growth banks (see e.g. Baron and Xiong, 2017; Fahlenbrach et al., 2017). Fahlenbrach et al. (2017), in particular, show that equity analysts systematically underestimate the risk associated with high loan growth rates.

Motivated by this empirical evidence, I ask whether equity investors' assessments of the risk associated with bank loan growth is influenced by the sentiment of bank managers. More specifically, I explore whether bank equity investors interpret the combination of a high loan growth rate and high bank manager sentiment as a signal for "healthy" loan growth, i.e. loan growth that creates value for the bank and its investors. I measure the equity market participants' assessment of bank risk by *SRISK* scaled by the enterprise value of the respective banks (see Section 3.3.4). Since it is based on equity market prices, *SRISK* is a forward-looking measure that is driven by market participants' assessments for the outlooks for cash flows and exposures to equity market risk. This leads me to the following hypothesis:

Hypothesis 1: Investors interpret high bank manager sentiment as a

Table 3.6: Is bank manager sentiment predictive of loan growth?

	(1)	(2)	(3)	(4)	(5)	(6)
	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$
$sent^*_{t-1}$	0.0746***		0.0658***		0.0519*	
	(0.0218)		(0.0218)		(0.0269)	
pos^*_{t-1}		0.0159		0.0096		-0.0053
		(0.0119)		(0.0127)		(0.0203)
neg^*_{t-1}		-0.0848***		-0.0797***		-0.0789**
		(0.0269)		(0.0289)		(0.0324)
$imputed$	0.1063	0.1020	0.0733	0.0698	-0.0136	-0.0109
	(0.1107)	(0.1106)	(0.1069)	(0.1069)	(0.1344)	(0.1340)
Constant	-0.0146	-0.0139	-0.0256*	-0.0256*	0.9157***	0.8984***
	(0.0106)	(0.0105)	(0.0133)	(0.0132)	(0.2241)	(0.2208)
Controls	No	No	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	No	No	No	Yes	Yes
Country-time fixed effects	No	No	No	No	Yes	Yes
N	2,251	2,251	2,211	2,211	2,211	2,211
R^2	0.0069	0.0092	0.0332	0.0355	0.2903	0.2927
Adj. R^2	0.0060	0.0080	0.0310	0.0330	0.1080	0.1100

Note: This table reports the results of separate regressions of loan growth on $sent^*$, pos^*, neg^* and bank-level and macroeconomic control variables. All variables are standardized. The control variables include $cash$, $secs$, and $reserves$. The variable *imputed* indicates whether missing values for an observation have been estimated via interpolation. The standard errors are clustered on the bank level and reported in parenthesis. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

positive signal for the risk associated with bank loan growth. Higher values of the bank manager sentiment index are negatively associated with the relationship between $SRISK$ and loan growth.

To test this hypothesis, I estimate the following model:

$$\begin{aligned} SRISK_{i,t} = SRISK_{i,t-1} &+ \alpha + \beta_1 \times loangrowth_{i,t-1} \\ &+ \beta_2 \times sent^*_{i,t} + \beta_3 \times sent^* *_{i,t-1} \times loangrowth_{i,t-1} \\ &+ \mathbf{X}_{i,t-1}\boldsymbol{\gamma} + u_i + v_t + w_{c,t} + \epsilon_{i,t}, \end{aligned} \tag{3.11}$$

where the vector $\mathbf{X}_{i,t} = \left(X^{profit}_{i,t}, X^{bm}_{i,t}\right)$ holds the bank-specific control variables used in the previous regressions and the variables u_i, v_t and $w_{c,t}$ are bank, time and country-time fixed effects, respectively. The coefficient of interest is β_3, which captures how the relationship between $SRISK$ and loan growth depends on the bank manager sentiment index.

I lag the explanatory variables by one period for two reasons. First, financial results and the corresponding press releases are typically released a few weeks after the end of the reporting period. Because the book value of total debt is an input in the calculation of *SRISK*, $SRISK_{i,t}$ is thus also observable only after the release of the financial statement. Second, to avoid that my results suffer from both hindsight bias and endogeneity problems, I use the next observable realization, $SRISK_{i,t+1}$ as my dependent variable. I also include the first lag of $SRISK$ as a control variable, given that it is highly persistent.

The regression results are documented in Table 3.7. All variables are standardized. Columns 1 and 2 of Table 3.7 report the results from nested versions of the model specified in Equation (3.11). These nested versions only include $loangrowth_{t-1}$ (column 1) and $loangrowth_{t-1}$ and $sent^*_{t-1}$ (column 2), respectively. The results reported in both columns suggest that none of the two variables are associated with $SRISK$, implying that bank equity investors neither consider loan growth nor the sentiment of bank managers when assessing the systemic risk of banks. When I distinguish by bank manager sentiment, however, I am able to detect a statistically significant relationship between bank loan growth and bank risk for banks with the most optimistic bank managers. The coefficient on the interaction between $loangrowth_{t-1}$ and $sent^*_{t-1}$ documented in column 3 of Table 3.7 suggests that an one standard deviation increase in $sent^*_{t-1}$ is on average associated with an 0.0130 standard deviations decrease in the coefficient on $loangrowth_{t-1}$. The model implies that the coefficient on $loangrowth_{t-1}$ is statistically significant at the 5% level when $sent^*_{t-1}$ is more than one standard deviation higher than its mean.

Since I include the first lag of the dependent variable as a control variable in my regressions, a concern with the results in columns 1–3 is dynamic panel bias (see also Section 3.5). To increase the robustness of my results, I re-estimate the specifications in columns 1–3 using the Arellano–Bover/Blundell–Bond system estimator. The results are reported in columns 4–6 of Table 3.7 and suggest that dynamic panel bias is an issue with the OLS results. Notable differences between the results from the Arellano–Bover/Blundell–Bond system estimator and that from the OLS estimator are that the coefficients on $sent^*_{t-1}$ in column 5 and the interaction term in column 6 are statistically significant at the 5%

level. The results in column 6 suggest that an one standard deviation increase in $sent^*_{t-1}$ is on average associated with an 0.0243 standard deviations decrease in the coefficient on $loangrowth_{t-1}$. The coefficient on the interaction between $loangrowth_{t-1}$ and $sent^*_{t-1}$ from the Arellano–Bover/Blundell–Bond system estimation thus has nearly double the size of that from the OLS estimation.[19]

In summary, the results documented in columns 3 and 6 of Table 3.7 are in support of my hypothesis that the sentiment of bank managers has a negative influence on how equity investors assess the risk associated with bank loan growth.[20] In both cases, the coefficients on the interaction between $loangrowth_{t-1}$ and $sent^*_{t-1}$ are negative and statistically significant at the 10% (OLS) and 5% (Arellano–Bover/Blundell–Bond) level, respectively, where the Arellano–Bover/Blundell–Bond system estimator yields the strongest negative interaction effect between the two variables. Given that dynamic panel bias might be an issue when estimating Equation (3.11), the estimates from the Arellano–Bover/Blundell–Bond system estimator are likely to have the lowest bias. I therefore consider the estimates reported in column 6 of Table 3.7 as the best estimate of the interaction effect between loan growth and the bank manager sentiment index.

Table 3.7: Does bank manager sentiment spill over to equity investors?

	(1) $SRISK_t$	(2) $SRISK_t$	(3) $SRISK_t$	(4) $SRISK_t$	(5) $SRISK_t$	(6) $SRISK_t$
$loangrowth_{t-1}$	-0.0204*	-0.0197	-0.0163	0.0013	0.0021	0.0074
	(0.0122)	(0.0120)	(0.0101)	(0.0101)	(0.0100)	(0.0093)
$sent^*_{t-1}$		-0.0135	-0.0124		-0.0196**	-0.0116
		(0.0104)	(0.0096)		(0.0090)	(0.0078)
$loangrowth_{t-1} \times sent^*_{t-1}$			-0.0130*			-0.0243**
			(0.0078)			(0.0102)
$SRISK_{t-1}$	0.6686***	0.6678***	0.6685***	0.4229***	0.4209***	0.4258***
	(0.0547)	(0.0546)	(0.0556)	(0.0596)	(0.0585)	(0.0554)
Constant	5.0103*	4.8342*	4.9164*	21.0017	21.0051	21.0112
	(2.7924)	(2.8091)	(2.7844)	(29.3188)	(29.9607)	(29.0984)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1169	1169	1169	1169	1169	1169
R^2	0.8685	0.8689	0.8695	NA	NA	NA
Adj. R^2	0.8100	0.8110	0.8110	NA	NA	NA

Note: This table reports the results from regressions of scaled $SRISK$ on $loangrowth$, $sent^*$ and bank-specific and macroeconomic control variables. The control variables include *impair*, *opinc*, *opexp*, *logta*, *loans*, *deposits*, *equity*, *intinc*, *gdp*, *infl*, *interbank*, *term*, *ois* and a dummy for whether values of an observations were interpolated. All variables are standardized. Specifications 1–3 are estimated with the fixed-effects estimator (OLS). The standard errors are clustered on the bank level and are reported in parenthesis. Specifications 4–6 are estimated with the Arellano–Bover/Blundell–Bond system estimator with robust standard errors. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

[19] Because the STATA command *xtdpdsys* I use for the Arellano–Bover/Blundell–Bond estimation of Equation (3.11) does not support STATA operators, I am currently not able to calculate confidence intervals for the estimates of the coefficients on $loangrowth_{t-1}$ conditional on $sent^*_{t-1}$. As a consequence, I am currently not able to report this information.

[20] In this context, a negative influence means lower risk.

3.7 Summary and Discussion

The aim of this paper was to provide evidence on how systematic over-optimism on the part of banks directly or indirectly affects the amount of credit that they supply to the real sector. Based on a measure of the sentiment of bank managers extracted from earnings press release documents – the bank manager sentiment index – I have documented that i) bank manager sentiment is partially backward-looking, i.e. it depends positively on past realizations of economic fundamentals, implying that it is on average too high relative to current fundamentals, ii) bank manager sentiment is on average positively associated with loan growth rates over the subsequent six months and iii) bank manager sentiment interacts with equity investors' assessments of the risk associated with bank loan growth in that, for a given loan growth rate, the banks with the most optimistic managers are perceived as less risky than the banks with the most pessimistic managers.

Taken together, these three findings suggest that systematic over-optimism on the part of banks and their investors affect credit market outcomes. More specifically, findings one and two suggest that decisions on the volume of new loans partially depend on past realizations of economic fundamentals. If this is the case, a financial stability implication will be that banks extend too much credit in a scenario where recent economic fundamentals were good, but where these fundamentals have already started to deteriorate. As a result, banks will be overly exposed to loan default risk, which threatens their solvency and adversely affects their ability to extend new loans. Findings one and three suggest that over-optimism on the part of bank managers also spills over to their equity investors, who then underestimate the risk associated with the loan growth decisions of banks. If this is the case, these lower risk assessments then will translate into lower costs of capital for banks, which in turn is positive for the banks' lending businesses.

As discussed in Section 3.3.1, my approach to extract textual sentiment scores from earnings press release documents has two weaknesses that need to be addressed to increase the robustness of my results. The first weakness is that I may falsely classify words that are preceded by a negation, which is the implication of my use of the bag-of-words approach. Since I have no estimate of how prevalent the use of negations in bank earnings press release documents is, I am also not able to assess whether and in which direction my use of the bag-of-words approach biases the the bank manager sentiment index. Addressing this weakness requires that I rewrite the algorithm that processes the earnings press release documents so that, for each word, it determines whether the preceding word is a negation. If this is the case, positive words need to be reclassified as negative words and vice versa.

The second, more severe weakness is that I am currently not able to determine to which reporting period a specific part of an earnings press release document relates to. Since I do not have this information, I cannot rule out that the correlations between the bank manager sentiment index and past realizations of economic fundamentals documented in this paper are just the result of bank managers also writing about earlier reporting periods and not the result of backward-looking expectation formation rules of bank managers. One option to address this weakness is that I modify the algorithm that processes the earnings press release documents so that it looks for keywords that provide information about the reporting period a specific text passage relates to (e.g. “full year” or “last year”). When all words are classified by reporting period, the next steps are to drop all words that do not refer to the current reporting period and to check whether all results still hold when I consider only words that relate to the main reporting period.

Another very interesting issue that I currently do not account for is that bank managers might be aware of investors’ increasing use of sentiment analysis tools and have started to strategically alter their language in their corporate disclosures so that they appear more optimistic than they actually are (see e.g. Huang et al. (2013) and Cao et al. (2020)). One possible implication of such a behavior in the context of this paper is that textual sentiment scores are biased upwards, whereas the biases are likely to be specific to each bank, depending on whether and when European bank managers have started to strategically manage the textual sentiment of their corporate disclosures. Moreover, my decision to define the bank manager sentiment index as the residuals from a regression of textual sentiment scores on a set of bank-specific and macroeconomic variables might introduce additional biases as the decision to begin managing the textual sentiment of corporate disclosures might alter the relationships between the resulting textual sentiment and economic fundamentals.

Interesting questions for future research thus are whether and to what extend bank managers strategically manage the textual sentiment of their corporate disclosures and whether investors eventually recognize such a behavior. In general, it would be very interesting to explore whether there is a feedback loop between how optimistic bank managers choose to appear and how investors assess current and future bank performance and risk.

Chapter 4

Do Financial Market Experts Know Their Theory? New Evidence From Survey Data

4.1 Introduction

Expected excess returns on risky assets, in particular on stocks, play a pivotal role in finance theory and practice. A good understanding of the properties of expected stock returns is, for example, required in the areas of portfolio management and corporate finance, where return forecasts are an important input to decisions on optimal portfolios and on whether a corporate project is a worthwhile investment (Cochrane, 2011). The existing empirical evidence based on realized stock returns suggests that expected stock returns are time-varying and counter-cyclical (Fama and French, 1989; Cochrane, 2011, 2017). Expected stock returns are considered as time-varying, because realized stock returns seem to be predictable by several (time-varying) macro-financial variables, one of the most prominent variable being the dividend–price ratio of the equity market (see e.g. Campbell (2000) and Welch and Goyal (2008) for a list of forecasting variables).[1] Because most of the variation in the dividend–price ratio of the equity market seems to be unrelated to the variation in dividends, the dividend–price ratio and related variables are interpreted as proxies for expected stock returns (Cochrane, 2011). Expected stock returns are considered to be counter-cyclical, because proxies for expected stock returns seem to be negatively correlated with measures of economic conditions (Fama and French, 1989).

However, evidence based on survey data, which has for a long time been

[1] The issue whether stock returns are predictable has not been settled yet. Welch and Goyal (2008), for example, argue that most of the financial variables that are considered to be predictors of stock returns fail to predict stock returns in out-of-sample tests of predictive power. Examples of papers defending stock return predictability are Campbell and Thompson (2008), Cochrane (2008), Rapach et al. (2010) and Ferreira and Santa-Clara (2011).

regarded as unreliable and redundant (Gennaioli et al., 2016; Manski, 2018; Giglio et al., 2019), is largely at odds with the evidence based on realized stock returns. The evidence suggests that expected stock returns are negatively correlated with variables that positively predict subsequent realized returns (e.g. Bacchetta et al., 2009; Greenwood and Shleifer, 2014; Amromin and Sharpe, 2014; Adam et al., 2017), that they negatively predict actual stock returns (e.g. Bacchetta et al., 2009; Greenwood and Shleifer, 2014; Amromin and Sharpe, 2014), that they are pro-cyclical (Amromin and Sharpe, 2014) and that they are extrapolative in recent returns on the stock market or returns on the portfolios of the respondents (e.g. Hurd et al., 2011; Greenwood and Shleifer, 2014; Barberis et al., 2015; Hoffmann and Post, 2017). Many authors in this strand of the literature therefore draw the conclusion that survey data of stock return expectations are inconsistent with the assumption of rational expectations.

Motivated by this contradictory evidence on the time-variation in expected stock returns, I use a unique survey dataset to study how financial market experts form their stock market expectations. I study survey measures of stock return expectations, because I regard them as more precise measures of expected stock returns than realized returns, given that the latter can be very noisy, for example, due to information surprises (Elton, 1999). I focus on financial market experts, because I expect their understanding of stock returns to be superior to that of households or individual investors, whose expectations are studied in the large majority of papers in the literature. I also expect the expectations of financial market experts to matter more for asset prices, given that institutional investors usually have a bigger impact on asset markets than private investors. Another reason is that the dataset that includes the stock market expectations of financial market experts has additional features that set it apart from other survey datasets studied in the existing literature. More specifically, the dataset is based on micro data from the ZEW Financial Market Survey (ZEW FMS, hereafter), which is a survey among German financial market experts, including professional stock market forecasters. The survey combines questions on macroeconomic and financial developments in Germany and other important economies, which makes it possible to study how the respondents' stock market expectations co-vary with their macroeconomic expectations. Moreover, in the survey, the respondents are asked to provide both qualitative and quantitative forecasts for the German DAX index in six months. This allows me to explore whether the question type matters for the results. Finally, the data on stock market expectations can be combined with personal information about the respondents. The information includes gender, age and indicators of the respondents' skill in forecasting stock returns, for example the respondents' main occupations or whether or not they are professional stock market forecasters.

The aim of this paper is threefold. First, I aim to get a better understanding of the sources of the variation in expected returns. I therefore follow Giglio et al. (2019) and decompose the variance of my quantitative survey measure of expected returns into three components: a component that captures the common time-series variation, a component that captures the variation across respondents and a component that captures the residual variance. The result of the variance decomposition indicates that respondents differ considerably in how they incorporate macroeconomic and financial information into their DAX forecasts. More specifically, I find that the component that captures the common time-series variation is the least important for explaining the total variation in my quantitative survey measure of expected returns, followed by the component that captures the variation across respondents. Together, these two components account for only a third of the total variation, implying that the remaining two thirds are idiosyncratic.

I then move on to study each of the three components in detail. I first explore to what extent the variation across respondents can be traced back to differences in the respondents' personal characteristics. The results suggest that all but one of the studied variables, i.e. birth year, career entry year, main occupation and whether the respondent is or has been a professional DAX forecaster, cannot account for this variation. The only characteristic that seems to be related to the variation across respondents is the self-assessed level of expertise in conducting DAX forecasts. To get a better understanding of the underlying drivers of the common time-series variation, I study the informational overlap with a set of macroeconomic and financial state variables I expect the respondents to consider when they forecast DAX returns. While the informational overlap ranges from non-existent to moderate, when each of the variables are evaluated on their own, they overlap strongly with the common time-series variation in expected returns when evaluated together. Surprisingly, the variable that shows the highest informational overlap is the return of the DAX over the month prior to the survey period. Finally, to illustrate the heterogeneity of how respondents incorporate information into their DAX forecasts, I exploit the long individual time-series in the ZEW FMS dataset and run respondent-level regressions of the quantitative survey measure of expected returns on my set of potential macroeconomic and financial determinants of DAX expectations. For the variables studied, I document considerable differences in R^2 statistics and a disagreement about the direction of the relationships with expected returns among respondents. Put differently, the respondents disagree about the importance of the variables for DAX returns and also about how these variables affect DAX returns.

Second, I aim to provide new evidence on the relationship between expected returns and economic conditions. More specifically, I explore whether expected returns are counter-cyclical, i.e. whether they are higher when economic conditions are bad and vice versa. As measures of economic conditions in Germany, I use the dividend–price ratio of the CDAX, the earnings–price ratio of the CDAX, the respondents' own assessments of the current economic situation in Germany and a composite economic indicator constructed from monthly indicators of German economic conditions. For comparability with the results of other studies, I first explore whether expected returns are counter-cyclical on average, i.e. I initially ignore the heterogeneity of the respondents' expectations. Motivated by the observation that previous studies in the literature are based on both types of expectation data, I also study both the respondents' quantitative and qualitative DAX expectations. An additional benefit of using both variables is that it allows me to investigate whether the result on the relationship between expected returns and economic conditions depends on the type of the expectation data used.

First, I find that, for some variables, the direction of the estimated relationship between economic conditions and DAX expectations depends on whether I use the qualitative DAX return forecasts or the quantitative DAX return forecasts. For example, the dividend–price ratio of the CDAX has a positive coefficient in the regression on the qualitative DAX return forecasts and a negative coefficient in the regression on the qualitative DAX return forecasts. As I am able to rule out that these differences either arise because respondents give answers to both questions that are inconsistent with each other or are the implication of outliers in the qualitative DAX return forecasts, the only remaining interpretation of the evidence is that the scale of the variable, i.e. metric vs. ordinal, matters strongly for the measured relationship between economic conditions and stock return expectations.

Second, focusing on the results for the quantitative forecasts, I find that the survey data is largely consistent with the hypothesis that stock return expectations are counter-cyclical. More specifically, I find that, for three out of the four considered measures of economic conditions, expected returns are on average higher when the measures indicate that economic conditions are bad, all else equal. Somewhat surprisingly, the only measure for which this is not the case, is the only subjective measure of economic conditions, which is the respondents' own assessments of current economic conditions in Germany. Furthermore, although it is only a control variable in the regressions, I also document a negative relationship between expected returns and the DAX return over the month prior to the survey. The evidence presented in previous studies, in contrast, suggests that stock return expectations are extrapolative in recent stock returns (see e.g. Greenwood and Shleifer, 2014; Barberis et al., 2015).

Third, I document minor differences in the relationships between DAX expectations and economic conditions across respondents. When I differentiate by age, I find that the correlation between the earnings–price ratio of the CDAX (which is higher when economic conditions are bad) and expected returns is decreasing with age. When I differentiate by the respondents' self-reported interest in the stock market results of the ZEW FMS, I find that the correlation between the composite economic indicator (which is lower when economic conditions are bad) and expected returns is only negative if the respondents report that they are interested. Lastly, when I differentiate by main occupation, I document that financial market experts across occupations seem to use different combinations of the measures of economic conditions when forecasting DAX returns, suggesting that, of all the characteristics explored, main occupation is the best differentiator when it comes to the relationship between DAX return expectations and measures of economic conditions.

Finally, the third aim of this paper is to evaluate the accuracy of the financial market experts' DAX return forecasts. An evaluation of the forecast accuracy is the natural next step, after I have studied how financial market experts form their stock return expectations. I begin by studying the aggregated quantitative forecast, which is the average expected DAX return by survey wave and the aggregated qualitative DAX return forecast, which is calculated as the difference between the shares of respondents that expect the DAX to increase and decrease, respectively, i.e. a so-called bull–bear spread. I find that the aggregate quantitative forecast is positively correlated with actual returns and explains about 6% of the variation in the latter. The aggregate qualitative forecast, in contrast, seems to be uncorrelated with actual returns. Both results are at odds with the finding of previous studies that survey measures of expected returns are negatively correlated with realized returns (see e.g. Greenwood and Shleifer, 2014).

Having shown that it is positively associated with realized returns, I next ask whether the aggregated quantitative DAX return forecast is superior in terms of forecast accuracy to the average historical return, the latter being an often used benchmark which stock return forecasts are compared to in the literature (see e.g. Welch and Goyal, 2008; Campbell and Thompson, 2008). I find that this is not the case, i.e. the use of the average historical DAX return produces DAX return forecasts that are at least as good as the aggregated DAX forecast from the ZEW FMS. As a final step, I explore whether there are differences in forecast accuracy within subgroups of the ZEW FMS panel formed by the various personal characteristics available to me. Most comparisons yield that the forecasts are equivalent in terms of accuracy. Interestingly, my results suggest that respondents who regularly conduct DAX forecasts outside of the ZEW FMS underperform those who do so only irregularly. In some cases, I also document differences in forecast accuracy when I distinguish by the respondents' main occupations. For example, during the sample period, respondents who have worked in "Trading" have provided DAX return forecasts that were closer to the actual realized returns than respondents who have worked in "Management". In all cases, however, the differences in forecast accuracy cannot be attributed to differences in how the respective groups form their DAX return expectations conditional on economic conditions.

To sum up, I document a strong disagreement among respondents about how important macroeconomic and financial variables are related to DAX returns. Despite this strong heterogeneity, the empirical evidence is largely in support of the view that expected returns are counter-cyclical. The two findings that weaken my results in this respect are that the respondents' own assessments of current economic conditions – the only subjective measure of economic conditions – are on average positively associated with expected returns and that the relationship between expected returns and economic conditions is not negative for all respondents. A methodological result is that the measured relationship between expected returns and economic conditions depends on whether I study qualitative or quantitative DAX return forecasts. Lastly, I find that the average quantitative DAX return forecast has predictive power for actual DAX returns, but is not superior to a simple average of historical DAX returns. However, because it is positively correlated with realized returns, the aggregated quantitative DAX return forecast from the ZEW FMS panel is a more accurate forecast than the survey measures of expected returns studied in the previous literature (e.g. Greenwood and Shleifer, 2014), which were found to be negatively correlated with realized returns.

The chapter proceeds as follows. Chapter 4.2 gives an overview of the literature to which this paper contributes. Chapter 4.3 introduces the ZEW Financial Market Survey, which is the main data source for this study and describes the composition of the associated panel of financial market experts. Chapter 4.4 gives more details about my two survey measures of stock return expectations and the other macroeconomic and financial variables studied in this paper. Chapter 4.5 contains the analysis of the sources of the variation in the quantitative DAX return forecasts. Chapter 4.6 explores whether expected returns are counter-cyclical. Chapter 4.7 studies the accuracy of the financial market experts' DAX return forecasts. Chapter 4.8 concludes.

4.2 Related Literature

This chapter contributes to different strands of the literature studying the determinants of stock return expectations using survey data. Table 4.1 gives an overview of different surveys studied in this literature. First, my paper contributes to the literature that is concerned with the relationship between survey measures of expected stock returns and variables that are considered to be proxies for expected returns. There is extensive empirical evidence in this literature that suggests that survey measures of expected returns are negatively correlated with these proxies. One of the first studies in this strand is Vissing-Jorgensen (2003), which documents that expected returns were high when the US stock market was high between 1998 and 2003. Follow-up studies by Bacchetta et al. (2009), Greenwood and Shleifer (2014), Amromin and Sharpe (2014) and Adam et al. (2017) find that survey measures of expected returns are negatively correlated with the dividend–price ratio of the stock market, the negative of surplus consumption[2] and the consumption–wealth ratio[3]. All three variables are, however, considered to be positively correlated with subsequent realized returns (Campbell and Cochrane, 1999; Lettau and Ludvigson, 2001; Cochrane, 2011). As shown by Greenwood and Shleifer (2014), this result holds for different survey measures of stock return expectations. They study six different survey measures which they find to be highly positively correlated with each other and negatively correlated with proxies for expected stock market returns. Lastly, Amromin and Sharpe (2014) document that survey expectations of stock returns are pro-cyclical, i.e. they are higher when economic conditions are good and vice versa, which is at odds with empirical evidence based on realized returns (see e.g. Fama and French (1989))) and the implications of consumption-based asset pricing models (e.g. Campbell and Cochrane (1999)). Söderlind (2010), in contrast, finds that survey forecasts of economists are higher in recessions. However, he also finds that expectations are negatively correlated with the dividend–price ratio.

My paper also contributes to the literature that documents systematic differences in stock return expectations across individuals. Dominitz and Manski (2004, 2007) study stock market expectation data from the Michigan Survey of Consumers and the Health and Retirement Study and find that expectations differ systematically by sex, age and schooling. Using the Michigan Survey of Consumers, Dominitz and Manski (2011) further show that the respondents differ in how they use available information to forecast stock returns.[4] Using data from the Health and Retirement Survey, Hudomiet et al. (2011) document an increase in the cross-sectional heterogeneity of expected returns after the US stock market crash of 2008, where the increase of the heterogeneity has been the highest for respondents who own stocks, for those who follow the stock markets and for those with higher average cognitive capabilities. Hurd et al. (2011) study data from the centER Panel and report lower expected returns for females and higher expected returns for active traders. Finally, Giglio et al. (2019) administer a survey among randomly selected U.S. based clients of Vanguard to study the link between the respondents' expectations and their portfolio hold-

[2]See Campbell and Cochrane (1999) for the definition of surplus consumption.

[3]See Lettau and Ludvigson (2001) for the definition of the consumption–wealth ratio.

[4]Glaser et al. (2019) show that the way how individuals use the information available to them to make a forecast also depends on how the information is presented to them.

Table 4.1: Overview of surveys studied in the literature

Survey	Participants	Availability of stock market expectations and frequency	Country of respondents / stock markets	Type of forecast	Authors
UBS/Gallup Investor Survey	households	1996–2007, monthly	USA/USA	quantitative	Vissing-Jorgensen (2003); Bacchetta et al. (2009); Greenwood and Shleifer (2014); Amromin and Sharpe (2014); Adam et al. (2017)
Stock Market Confidence Indices, International Center for Finance, Yale School of Management	wealthy individuals, institutional investors	1989–, monthly	USA/USA, Japan/Japan	qualitative	Bacchetta et al. (2009)
The CFO Survey (Graham and Harvey)	financial professionals	1998–, quarterly	USA/USA	quantitative	Greenwood and Shleifer (2014)
The American Association of Individual Investors Investor Sentiment Survey	individual investors	1987–, weekly	USA/USA	qualitative	Greenwood and Shleifer (2014)
Survey of Consumers, Michigan University	households	2000–2005, monthly	USA/USA	quantitative	Dominitz and Manski (2004, 2011); Greenwood and Shleifer (2014); Amromin and Sharpe (2014)
Livingston Survey	economists	1946–, monthly	USA/USA	quantitative	Söderlind (2010)
centER	households	2004, 2006	Netherlands/Netherlands	quantitative	Hurd et al. (2011)
Health and Retirement Study	households	2002–, bi-annually	USA/USA	quantitative	Dominitz and Manski (2007); Hudomiet et al. (2011)
Giglio et al. (2019)	clients of Vanguard	2017–2019, bi-monthly	USA/USA	quantitative	Giglio et al. (2019)

ings. They decompose the variance of their measure of stock return expectations and find that the majority of the variation is explained by person fixed effects. Giglio et al. (2019) further explore whether the person fixed effects in expected returns can be traced back to observable personal characteristics like gender or age etc., but find that this is not the case.

Lastly, my paper is related to research that evaluates the predictive power of stock market forecasts obtained from survey data. Bacchetta et al. (2009) study survey data from UBS/Gallup and the ICF of the Yale School of Management and find that variables that forecast realized returns – the dividend–price ratio of the stock market in particular – are negatively correlated with the forecast errors made by the respondents. Deaves et al. (2010) use the ZEW FMS dataset to study 90% confidence intervals for stock returns. They find that, during the sample period between 2003 and 2005, the percentage of respondents, for which the respective confidence interval contained the realization of the DAX, ranges from around 10% to about 80%. In a follow-up study, Deaves et al. (2019) document that the mean forecast for the excess DAX return explains about 6% of the variation in actual DAX returns out-of-sample. Söderlind (2010) analyzes the forecasting performance of the Livingston Survey and reports that the median forecast has no explanatory power for realized returns out-of-sample. Finally, Greenwood and Shleifer (2014) document a weak and negative relationship between the survey measures of expected returns studied by them and subsequent realized returns. They attribute this result to the negative relationship between survey expected returns and proxies for expected return.

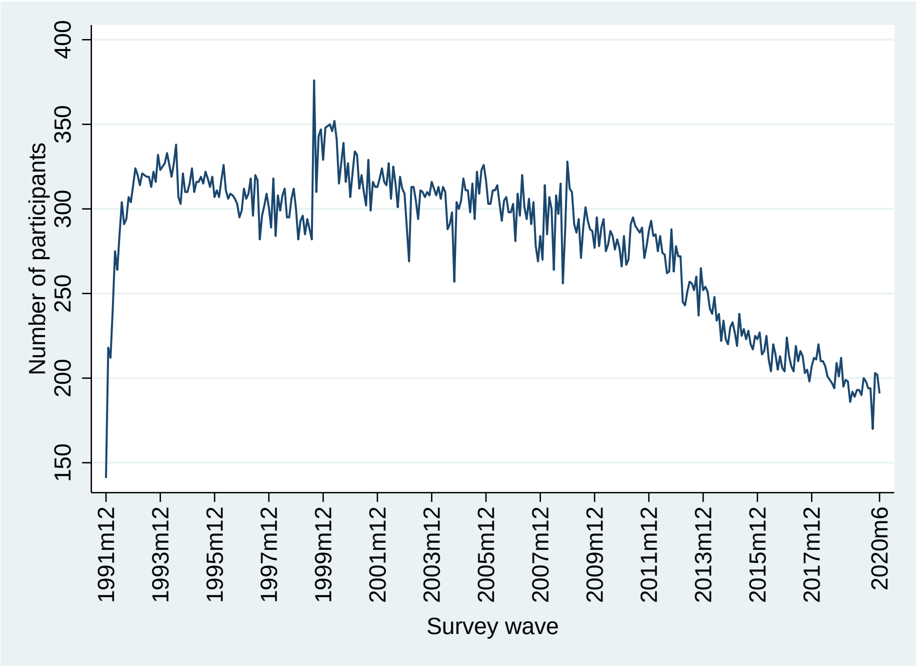
4.3 The ZEW Financial Market Survey

My main data source is the ZEW Financial Market Survey (ZEW FMS). The ZEW FMS is a monthly panel survey among German financial market experts that covers macroeconomic and financial developments in Germany and other important countries. The panel members are predominantly Germans who work in financial institutions and corporate finance departments of non-financial companies in Germany. The ZEW FMS was first conducted in December 1991 and is still running. Until the end of 2019, the length of each survey period was two weeks. Since 2019, it has been one week. As of June 2020, the number of monthly participants has ranged from 141 to 376 since the beginning of the survey. The time series of the monthly participants is depicted in Figure 4.1.

Important features of the survey design are that the survey is anonymous and that the participants receive as a non-monetary compensation for taking part the aggregated results, as well as a short report with comments on the most important results. The anonymity of the participants is important because the participants might otherwise be discouraged from reporting their true expectations (Croushore, 1993). Given that the ZEW FMS has a high international media coverage and is closely followed by economists and by finance practitioners, receiving the survey results for free likely is sufficiently valuable to motivate the financial experts to participate. Moreover, the participants receive the results prior to the release on the ZEW website.

The survey questions cover macroeconomic and financial developments in Germany, France, Italy, the Eurozone, Great Britain, the USA and Japan. The questionnaire consists of a set of regular questions and one or more extra ques-

Figure 4.1: Monthly number of participants of the ZEW FMS



tions, with varying topics. In the regular macroeconomic questions, the participants are asked to provide their assessments of current economic conditions, as well as their medium-term expectations regarding economic growth and inflation. The regular financial questions cover the participants' medium-term expectations with respect to short-term and long-term interest rates, exchange rates, the price of oil and important stock market indices.

The questionnaire includes three questions about the German DAX index. The results to these questions are the focus of this paper. The first question asks the participants to provide a qualitative forecast of the level of the DAX in six months. More specifically, the participants are asked whether they expect the DAX to "increase", "not change" or "decrease". This question has been asked since 1991. The second question asks the participants to provide a point forecast, as well as the lower and upper bounds of a 90% confidence interval, for the DAX in six months. This question was added to the questionnaire in 2003. The third question is concerned with the current level of the DAX and was added in 2011. In this question, the participants are asked whether they think that DAX is currently "fairly-valued", "over-valued" or "under-valued" in view of the current fundamentals of the DAX companies.

4.3.1 Panel Composition

On entry to the ZEW FMS panel, the participants are asked to provide details about themselves. These details are only available to researchers. The personal details include gender, age, career entry year and the highest achieved educational degree. Personal characteristics are occasionally also collected retrospectively. Examples are the respondents professional occupation, whether the respondents are currently or have been professional DAX forecasters in the past and the participants' self-assessed levels of expertise in answering the ZEW FMS questions. Unfortunately, not all of these details are available for every panel member. Reasons are that the collection of personal details only began after the start of the survey and that the panel members do not have to answer these questions, so some decide not to.

Figures 4.2 and 4.3 illustrate how the ZEW FMS panel is composed in terms of gender, birth year, main occupation and professional experience in stock market forecasting. Since the group of respondents fluctuates from month to month, I document both the composition of the full panel, i.e. that of all current and past participants, as well as the composition by survey wave. As of June 2020, the dataset includes responses of a total of 1,971 different participants. Panels 4.2a and 4.2b of Figure 4.2 show the panel composition by gender. For about 70% of the panel members, gender is unknown. As Panel 4.2b reveals, the information about gender is mainly missing for panel members that were active before the year 2010.[5] It is also revealed that gender is highly unevenly distributed in the panel: of the 30% of panel members with known gender, about 93% are male.

Panels 4.2c and 4.2d of Figure 4.2 depict the panel composition by birth year. The distribution of birth years ranges from 1938 to 1990, with a median of 1965 (Panel 4.2c). Over the years, the distribution of birth years has moved upwards, i.e. the median birth year has increased from around 1955 to 1965, while the differences between the 25th percentile, the median and the 75th percentile have remained largely stable (Panel 4.2d). The upward movement suggests that participants exiting the panel are usually replaced by younger participants. The share of participants for which the birth year is unknown, is also very high in the beginning of the sample period and decreases to under 50% over time.

Panels 4.3a and 4.3b of Figure 4.3 display the panel composition by main occupation. The variables for main occupation combine the results of special surveys from 2011 and 2020. More specifically, if respondents had a given main occupation in either 2011 or 2020, I assume that they had this main occupation during the full sample period. A respondent thus can have multiple main occupations. The information on occupation is available for about 17% of the panel members. As can be seen in Panel 4.3b, the availability of the information on main occupation is mainly restricted to the current field of participants. The three most frequent main occupations are "Fund Management", "Economic Research" and "Wealth Management".

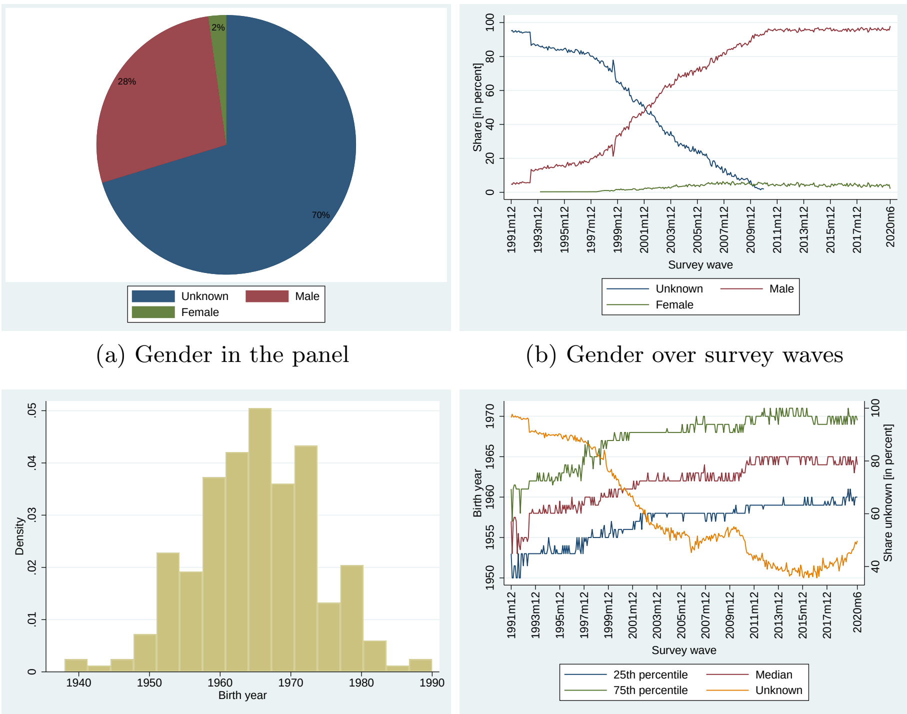
Finally, Panels 4.3c and 4.3d of Figure 4.3 present the panel composition by professional experience in stock forecasting. The variable can take the values "regular", "sometimes" and "never", which refers to the frequency of the respondents' DAX forecasting activities outside of the scope of the ZEW FMS. The variable combines the results of special surveys from 2013 and 2020. Similar to the assumptions with respect to main occupation, I assume that respondents had a high professional experience, i.e. regularly forecasted the DAX outside of the scope of the ZEW FMS, when they answered so in either 2013 or 2020.[6] As Panel 4.3c reveals, details on professional stock market forecasting activities are

[5]However, it should be possible to infer the gender from the panel members' names, which are available. I leave this for future projects.

[6]The option "sometimes" was only available in the surveys in 2020.

available for about 43% of the panel members. While 20% of panel members have never conducted DAX forecasts outside of the scope of the ZEW FMS, 16% and 7% have done so regularly or irregularly, respectively. In recent years, the share of participants that regularly and professionally forecasts the DAX has fluctuated around 30% (see Panel 4.3d).

Figure 4.2: Panel composition: gender and birth year



(a) Gender in the panel

(b) Gender over survey waves

(c) Birth year in the panel

(d) Birth year over survey waves

Notes: These figures illustrate the compostion of the ZEW FMS in terms of gender and birth year. The figures on the left show the composition of the full panel, i.e. all current and past participants of the ZEW FMS. The figures on the right show how the composition has evolved over time.

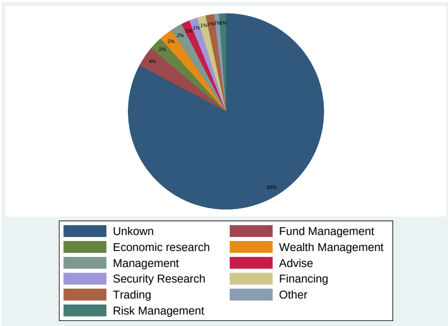
4.4 Data And Data Preparation

This section introduces the variables I use in this paper. These include my two survey measures of DAX return expectations, the macroeconomic and financial variables used to measure economic conditions and macroeconomic and financial control variables.

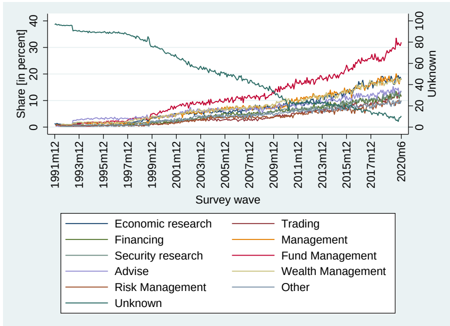
4.4.1 Survey Measures Of DAX Return Expectations

My main variable of interest is the expectation of the return of the DAX over the next six months, obtained from the ZEW FMS. Because the respective question in the survey asks the participants to provide a forecast of the level of the DAX

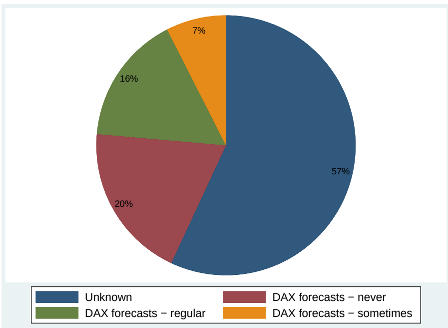
Figure 4.3: Panel composition: main occupation and professional experience in stock market forecasting



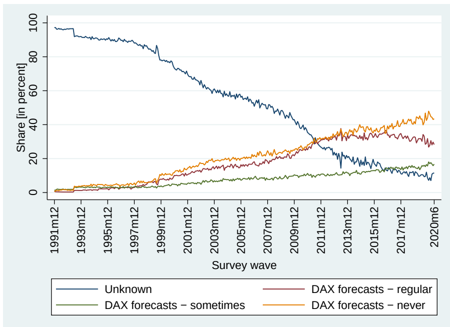
(a) Main occupation in the panel



(b) Main occupation across survey waves



(c) Professional experience in stock market forecasting in the panel



(d) Professional experience in stock market forecasting across survey waves

Notes: These figures illustrate the compostion of the ZEW FMS in terms of main occupation and professional experience in stock market forecasting. The figures on the left show the composition of the full panel, i.e. all current and past participants of the ZEW FMS. The figures on the right show how the composition has evolved over time.

in six months, the level forecast needs to be transformed into a return first. I define the return forecast implied by the level forecast as

$$expret_{i,s,t} = \frac{E_{i,t}[P^{DAX}_{t+6m}]}{P^{DAX}_t} - 1, \tag{4.1}$$

where $E_{i,t}[P^{DAX}_{t+6m}]$ is the point forecast of the level of the DAX in six months of respondent i on date t and P^{DAX}_t is the latest closing level of the DAX available at date t. In some cases, it was necessary to clean the DAX forecasts $E_{i,t}[P^{DAX}_{t+6m}]$ prior to the calculation of the implied return. In these cases, I have applied the following adjustment rules to the raw data. First, if a respondent abbreviated numbers, the forecast was multiplied by an appropriate factor. A forecast of 12.5, for example, was multiplied by the factor thousand, resulting in the forecast 12,500. Second, if the 90% confidence interval for the DAX in six months provided by a respondent did not contain his or her DAX expectation, it was assumed that middle response of the three values is the actual DAX expectation. To minimize the effect that these manual adjustments have on my results, I include the variable *corrected* in all of my analyses, which takes the value of one if the original DAX expectation has been corrected and zero otherwise.

For comparability with the results of other studies, I also study the financial market experts' qualitative forecasts of the DAX in six months, which I refer to as *expdir*. In the respective question, the survey participants are asked whether they expect the DAX to "increase", "not change" or "decrease" over the next six months, thus $expdir_{i,s,t} \in \{increase, notchange, decrease\}$. Qualitative stock return forecasts of this type are usually aggregated by calculating the difference between the share of respondents who expect the DAX to increase and the share of respondents who expect the DAX to decrease, i.e. a so-called bull–bear spread. I will follow this convention when I study survey expectations of DAX returns at the aggregated level in Chapter 4.7.1.

4.4.2 Other Data

To obtain a better understanding of the determinants of the respondents' DAX expectations, I relate my survey measures of expected returns to a set of macroeconomic and financial state variables, as well as to the respondents' answers to other questions from the ZEW FMS. My variable selection is thereby guided by asset pricing theory and empirical evidence. I distinguish between four groups of explanatory variables. Table 4.2 contains a list of all variables used in the empirical analyses.

The first group includes variables that are considered to be predictive for realized returns. The two variables in this group are the dividend–price ratio (*dp*, hereafter) and the earnings–price ratio (*ep*, hereafter) of the equity market. As the relevant measure of the German equity market, I use the CDAX index. I consider *dp*, because the dividend–price ratio is one of the most studied proxy variable for expected stock returns in the literature (see e.g. Cochrane, 2008, 2011) and therefore also studied in Greenwood and Shleifer (2014) and Amromin and Sharpe (2014). I additionally consider the earnings–price ratio, because there seems to have been a disconnect between earnings and dividends before the financial crisis of 2007–2009 (see Chapter 4.6.1), which has implica-

Table 4.2: List of macroeconomic and financial covariates

Variable	Abbreviation	Source	Comments
Log dividend–price ratio, CDAX	*dp*	Eikon Datastream (CDAXGEN)	Datatype: DSDY
Log earnings–price ratio, CDAX	*ep*	Eikon Datastream (CDAXGEN)	Datatype: DSPE
Industrial production, Germany	*ipgrowth*	Eikon Datastream (BDIPTOT.G)	Year-on-year growth rate; inflation, calendar and seasonal adjusted; publication lag: 2 months
Employment rate, Germany	*empl*	Eikon Datastream (BDUN%TOTR)	Calculated as 1−unemployment rate; in percent of civilian labor force; publication lag: 1 month
Inflation rate, Germany	*infl*	Eikon Datastream (BD-CPANNL)	Year-on-year change in prices; publication lag: 1 month
Consumer confidence, Germany	*conf*	Eikon Datastream (BD-CNFCONQ)	Based on European Commission consumer survey; publication lag: 1 month
Price of crude oil	*oil*	Eikon Datastream (CRUDBFO)	European Brent Spot
Exchange rate US-Dollar to Euro	*exchrate*	Eikon Datastream (USEURSP)	
DAX return - 12 months to 3 months prior to date t	*dax12to3*	Eikon Datastream (DAXINDX)	Datatype: RI
DAX return - 3 months to 1 month prior to date t	*dax3to1*	Eikon Datastream (DAXINDX)	Datatype: RI
DAX return - 1 month prior	*dax1to0*	Eikon Datastream (DAXINDX)	Datatype: RI
Assessment of the current economic situation, Germany	*sit*	ZEW FMS dataset	Ordinal variable, response options: “good”, “normal”, “bad”
Outlook for economic situation, Germany (6 months)	*expsit*	ZEW FMS dataset	Ordinal variable, response options: “improve”, “not change”, “worsen”
Outlook for inflation rate, Germany (6 months)	*expinfl*	ZEW FMS dataset	Ordinal variable, response options: “improve”, “not change”, “decrease”
Outlook for short-term interest rates, Eurozone (6 months)	*expint_st*	ZEW FMS dataset	Suggested reference in questionnaire: “3-month interbank rates”; ordinal variable, response options: “improve”, “not change”, “decrease”
Outlook for long-term interest rates, Germany (6 months)	*expint_lt*	ZEW FMS dataset	Suggested reference in questionnaire: “yields on 10-year bonds”; ordinal variable, response options: “improve”, “not change”, “decrease”

tions for my results in Chapter 4.6. Two other, potentially interesting forecasting variables studied in Greenwood and Shleifer (2014) are the consumption-wealth-ratio (Lettau and Ludvigson, 2001) and the surplus–consumption ratio (Campbell and Cochrane, 1999). These are, however, unavailable to me.[7]

The second group includes variables that contain information about the current state of the German economy. Because variables considered to be predictive for stock returns seem to move with business cycles (see e.g Fama and French, 1989; Cochrane, 2017), Amromin and Sharpe (2014) study the correlations between their survey measure of expected returns and measures of economic conditions. Following Amromin and Sharpe (2014), I study the respondents' own assessment of the current economic situation in Germany from the ZEW FMS dataset. I also consider the following economic indicators for Germany: the year-on-year growth rate of industrial production (*ipgrowth*), the employment rate (*empl*), the year-on-year growth rate of the German Consumer Price Index (*infl*), a consumer confidence indicator (*conf*), the exchange rate between US dollars and the euro (*exchrate*) and the price of crude oil (*oil*). Most of the economic indicators have a publication lag, meaning that the respondents learn the realizations of these variables only after one or two months. Since I would otherwise compare the DAX expectations to the realizations of the economic indicators that were unknown to the respondents at the time of the response, I shift these variables by their respective publication lag.

The third group encompasses the respondents' answers to forward-looking questions regarding the German economy from the ZEW FMS dataset. These are the respondents' outlooks with respect to the general economic situation, the inflation rate, short-term interest rates and long-term interest rates. I include these variables because they are likely correlated with the respondents' assessment of the current economic situation, which is a key explanatory variable for expected returns in Chapter 4.6. Moreover, the results of Amromin and Sharpe (2014) suggest that these variables might themselves be important explanatory variables for DAX expectations.

The fourth group includes past DAX returns. Past returns have been shown to explain survey expectation of stock returns (see e.g. Greenwood and Shleifer, 2014; Barberis et al., 2015). Here I consider the return of the DAX up to 12 months prior to each response and split the 12–month return into three parts: the return from $m_s - 12m$ to $m_s - 3m$ (*dax12to3*), the return from month $m_s - 3m$ to $m_s - 1m$ (*dax3to1*) and the return from month $m_s - 1m$ up to the day of the response (*dax1to0*), where m_s is the month of survey wave s.

4.5 Understanding The Sources Of The Variation In Expected Stock Returns

In this section, I study the sources of the variation in my quantitative survey measure of DAX return expectations, *expret*. I follow Giglio et al. (2019) and decompose the variance of *expret* into three components. The first component captures the common variation in *expret* over time, for example, due to changes

[7]With respect to the consumption–wealth ratio, I lack the information about the wealth of German households. To obtain the surplus–consumption ratio, it is necessary to calibrate the habit-model to the German economy. The benefit of this calibration is only minor.

in the general macroeconomic and financial environment and is obtained by regressing *expret* on either survey fixed effects or time fixed effects, where time fixed effects are fixed effects for the specific days on which the participants completed the questionnaire. While survey fixed effects only capture the time-series variation across survey waves, time fixed effects additionally capture the time-series variation within survey waves. Under the assumption of rational expectations and the absence of private information, most of the variation in expected returns is driven by this component (Manski, 2018). The corresponding regression models are

$$expret_{i,s,t} = \sum_{s=1}^{S} \phi_s D_s + \epsilon_{i,t} \tag{4.2}$$

$$expret_{i,s,t} = \sum_{t=1}^{T} \phi_{s,t} D_{s,t} + \epsilon_{i,t}, \tag{4.3}$$

where $expret_{i,s,t}$ is the implied quantitative DAX return expectation of respondent i on date t in survey wave s for a horizon of six months and ϕ_s and $\phi_{s,t}$ are the survey and time fixed effects, respectively. Note that date t is always uniquely associated with a survey wave (e.g. June 2020) which is indexed by s. The indices s and i thereby run from 1 to the number of survey waves, S and the number of survey days, T, respectively. To avoid that my results on the importance of time fixed effects are driven by days with low numbers of responses, I exclude all survey days where the number of responses is lower than 30 when estimating Equation (4.3).

The second component captures systematic differences in the overall level of *expret* in the cross-section of respondents, for example because some respondents are generally optimistic or pessimistic and is obtained by regressing *expret* on respondent fixed effects. The corresponding regression model is

$$expret_{i,s,t} = \sum_{i=1}^{I} \phi_i D_i + \epsilon_{i,s,t}, \tag{4.4}$$

where ϕ_i is the fixed effect of respondent i and I is the total number of respondents in the ZEW FMS panel.

The third component is the residual variance in a regression of *expret* on survey and respondent fixed effects or time and respondent fixed effects. The residual variance can be attributed to either idiosyncratic changes in expectations over time or noise (Giglio et al., 2019). The corresponding regression models are

$$expret_{i,s,t} = \sum_{s=1}^{S} \phi_s D_s + \sum_{i=1}^{I} \phi_i D_i + \epsilon_{i,t} \tag{4.5}$$

$$expret_{i,s,t} = \sum_{t=1}^{T} \phi_{s,t} D_t + \sum_{i=1}^{I} \phi_i D_i + \epsilon_{i,t}. \tag{4.6}$$

Table 4.3 reports the R^2 statistics from estimated models (4.2) to (4.6). Columns 1 and 2 of Table 4.3 reveal that survey and time fixed effects account for only about 10.5% and 12.7%, respectively, of the variation in *expret*, adjusted for the degrees of freedom. The result that time fixed effects explain a larger share of the variance of *expret* than survey fixed effects indicates that the respondents' information sets relevant for DAX forecasts change on a daily basis and may change considerably during a given survey period, which has to be considered when aggregating forecasts. Column 3 shows that the adjusted R^2 statistic for respondent fixed effects is 23.4%. While respondent fixed effects explain a larger share of the variance of *expret* than survey or time fixed effects, the share explained is significantly lower than that measured in other survey datasets. Giglio et al. (2019), for example, find that person fixed effects account for nearly 60% of the variation in their survey measure of expected returns. Finally, the (adjusted) R^2 statistics reported in columns 4 and 5 imply that the majority of the variation in *expret* has to be attributed to idiosyncratic changes in expectations and noise: the combinations of survey and respondent fixed effects, as well as time and respondent fixed effects, explain only 33.3% and 36.3%, respectively, of the variance in *expret*.

Table 4.3: Variance decomposition of *expret*

Dependent variable: *expret*	Survey fixed effects	Time fixed effects	Respondent fixed effects	Survey & respondent fixed effects	Time & respondent fixed effects
R^2	10.9%	14.7%	24.7%	34.7%	39.5%
Adj. R^2	10.5%	12.7%	23.4%	33.3%	36.3%
N	45,605	26,251	45,605	45,605	26,251
Comments		#responses $\geq$30			#responses $\geq$30

Notes: This table reports the results of separate regressions of *expret* on survey fixed effects, time fixed effects and respondent fixed effects. The dependent variable *expret* has been orthogonalized with respect to the variable *corrected*. In the regressions that include time fixed effects as independent variables, all observations were excluded for which the number of total responses on the day on which the respective response was submitted is below 30.

4.5.1 Decomposing Respondent Fixed Effects

Having quantified the relative importance of the three components of the variance of *expret*, I move on to study the three components in detail. To shed more light on the component that captures the variation in *expret* across respondents, I ask to what extent the variation in the estimated respondent fixed effects, $\hat{\phi}_i$, are explainable by differences in the respondents' observable characteristics. Available characteristics are the respondents' birth years, career entry years, their main professional occupations, whether they are currently or were professional DAX forecasters in the past and their own assessments of their level of expertise in forecasting the DAX. Because this information has been collected in different surveys, the number of observations for each characteristic varies considerably. The corresponding regression model is

$$\hat{\phi}_i = \alpha + x_i\beta_i + \epsilon_i, \tag{4.7}$$

where $\hat{\phi}_i$ is the estimate of respondent i's fixed effect, x_i is a row vector holding the characteristic and β_i is a column vector holding the coefficient.

Table 4.4 documents the R^2 statistics from separate regressions of the estimated respondent fixed effects on respondent characteristics. The first two columns reveal that the variables *birth year* and *career entry year* do not explain the variation in respondent fixed effects. The occupation variables in the third column imply a R^2 statistic of about 11%, which shrinks to almost 0% when it is adjusted for the number of variables. With an adjusted R^2 statistic of about 3%, the categorical variable indicating whether the respondent is currently or was a professional DAX forecaster has small explanatory power for the variation in the estimated respondent fixed effects (fourth column). The respondents' own assessment of their level of expertise in forecasting the DAX produces an adjusted R^2 statistic of 6.6% (fifth column) and is therefore the variable that explains the largest share of the cross-sectional variance of respondent fixed effects. Finally, the model that includes all variables yields a R^2 statistic of about 55% (sixth column). However, the high R^2 statistic is mainly the implication of the large number of variables relative to the number of observations (only 58). Adjusted for the number of variables, the R^2 statistic is about 14%. In summary, differences in the respondents' observable characteristics account for only a small share of the variation in *expret* across respondents. Variables that proxy for the respondents' experience in conducting DAX forecasts have the highest explanatory power for the cross-sectional variance of respondent fixed effects.

4.5.2 Common Time-series Variation

The results of the variance decomposition of *expret* indicate that between about 10.5% (for survey fixed effects) and about 12.7% (for time fixed effects) of its variation can be attributed to common times-series variation. In this section, I attempt to identify the macroeconomic and financial determinants of *expret* that are captured by this component. I consider a variable as a potential driver of the common variation in *expret* if there is a considerable informational overlap between the variable and survey or time fixed effects. To quantify the informational overlap, I compare the adjusted R^2 statistic from the regression of *expret* on the candidate variable to that from the regression of *expret* on the candidate variable plus survey or time fixed effects. The difference in adjusted R^2 then indicates how much of the common time-series variation in *expret* is explained by the candidate variable. In other words, the smaller the increase in adjusted R^2 when survey or time fixed effects are added to the model, the higher is the informational overlap and the more important is the variable for explaining the common variation in *expret*.

I consider the following macroeconomic and financial variables as potential drivers of the common variation in *expret* over time. The macroeconomic variables are *ipgrowth*, *empl*, *infl* and *conf*. Given that these variables do not vary

Table 4.4: Variance decomposition of respondent fixed effects

Dependent variable: respondent fixed effects	Birth year	Career entry year	Occupation	Professional forecasting activities	Expertise DAX forecasts	All variables
R^2	0.0%	0.0%	10.7%	3.4%	10.9%	54.5%
Adj. R^2	-0.04%	-0.04%	0.8%	2.7%	6.6%	13.6%
N	256	253	191	281	132	58

Note: This table reports the results of separate regressions of estimates of the respondents' fixed effects on their personal characteristics. The dependent variable *expret* has been orthogonalized with respect to the variable *corrected*.

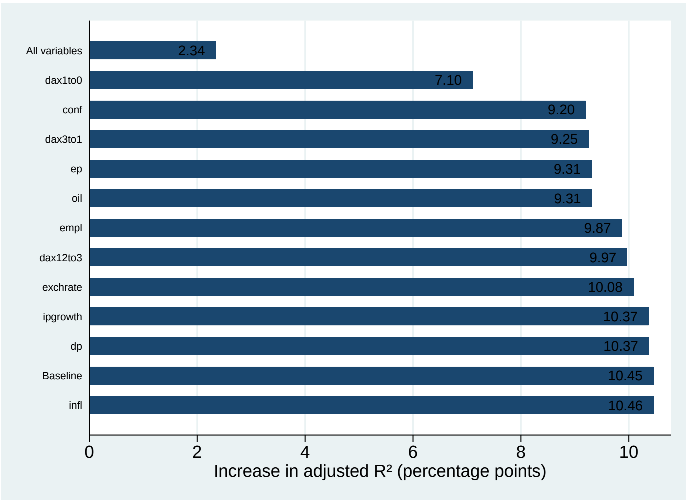
within surveys, I only consider them in the analysis of survey fixed effects.The financial variables are *dp*, *ep*, *exchrate*, *oil*, *dax12to3*, *dax3to1* and *dax1to0*. Since these financial variables have a daily frequency and thus vary also within survey waves, I use survey averages in my analysis of survey fixed effects.

Figure 4.4 documents the informational overlap between the macroeconomic and financial variables and survey and time fixed effects. The overlap with survey fixed effects is depicted in Figure 4.4a. Each bar represents the increase in adjusted R^2 when survey fixed effects are added to a regression of *expret* on the respective variable(s). The baseline model only includes survey fixed effects and is the benchmark against which the other models are compared. I also evaluate the model that includes all considered candidate variables. The results are the following. The variable with the least overlap with survey fixed effects is *infl*. When survey fixed effects are added to the regression of *expret* on *infl*, the adjusted R^2 increases by about 10.46 percentage points. The result that the increase is larger than the adjusted R^2 statistic of the baseline model indicates that variation in *infl* is unrelated to the time-series variation in *expret*. With an increase of about 7.10 percentage points, the variable with the highest overlap with survey fixed effects is the return of the DAX over the month prior to dates when the responses are submitted, averaged by survey wave, *dax1to0*. As the first bar illustrates, the model that includes all variables has the highest overlap with survey fixed effects. When survey fixed effects are added to this model, the increase in the adjusted R^2 is only about 2.34 percentage points, suggesting that these variables are direct or indirect drivers of the common time-series variation in *expret*. However, the large difference between the increase in adjusted R^2 for the full model and the increases in the adjusted R^2 for the individual variables, suggests that informational overlap across the considered macroeconomic and financial variables is rather small. Interestingly, *dp*, which should be one of the most important variables, ranks very low and is able to explain only a very small share of the common time-series variation in *expret*. The earnings–price ratio (*ep*), in contrast, does relatively better, but still has a smaller informational overlap with survey fixed effects than, for example, *conf*.

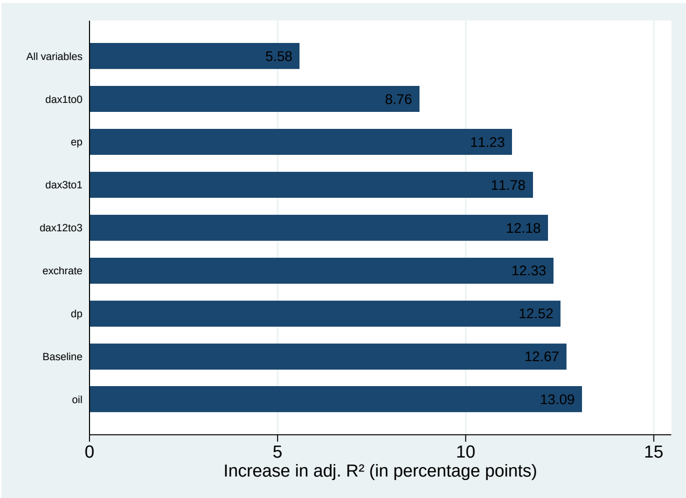
Figure 4.4b documents the overlap between the financial candidate variables and time fixed effects. As before, I dropped all survey period days, on which the total number of responses is below 30. Qualitatively, the results are similar to those from the analysis of survey fixed effects. Again, *dax1to0* is the variable with the highest overlap with time fixed effects. The variable *ep* performs better than *dp*, the latter showing only little overlap with time fixed effects. Finally, the combination of all investigated variables shows a sizable informational overlap with time fixed effects. Adding these fixed effects to the full model leads to an increase in the adjusted R^2 of about 5.58 percentage points versus an increase of about 12.67 percentage points for the baseline model. The overlap is, however, smaller than in the analysis of survey fixed effects, in which the increase for the full model was only about 2.34 percentage points, but where the full model also includes the macroeconomic variables.

To sum up, none of the considered variables shows a significant informational overlap with survey and time fixed effects when considered on their own. The variable with the highest overlap is *dax1to0*. Only when considered together, the variables account for the majority of the common variation in *expret* over time.

Figure 4.4: Measuring the informational overlap between survey and time fixed effects and potential determinants of *expret*



(a) Survey fixed effects



(b) Time fixed effects

Note: Figures 4.4a and 4.4b document the increases in adjusted R^2 when survey fixed effects (Figure 4.4a) and time fixed effects (Figure 4.4b), respectively, are added to regressions of *expret* on the variables on the vertical axes. Lower values are interpreted as a higher informational overlap between the respective variables and survey or time fixed effects. *Baseline* refers to the model that only includes survey fixed effects (Figure 4.4a) or time fixed effects (Figure 4.4b). The variables *dax1to0*, *dax3to1*, *dax12to3*, *ep*, *dp*, *oil* and *exchrate* in Figure 4.4a are survey wave averages. The variables *ipgrowth*, *infl*, *conf* and *empl* in Figure 4.4a have been shifted by their respective publication lags. Figure 4.4b only reports the increases in adjusted R^2 for values that have a daily frequency. Moreover, all observations for which the number of total responses on the days, on which the respective response was submitted is below 30 have been excluded.

4.5.3 Idiosyncratic Variation

Finally, I turn to the idiosyncratic component, which accounts for the highest share of the variance of *expret*. The high importance of this component indicates a large heterogeneity of how respondents incorporate information into their DAX forecasts. To shed more light on this heterogeneity, I exploit the long respondent-level time series available in the ZEW FMS dataset and run separate respondent-level regressions of *expret* on the macroeconomic and financial variables already studied in Chapter 4.5.2, as well as the respondents' own assessments of the current and future situation of the German economy from the ZEW FMS dataset. For a better comparability with other variables, I treat categorical ZEW FMS variables as continuous variables. Moreover, to obtain meaningful estimates, I exclude all respondents that have responded less than 30 times in total. For the remaining sample of respondents, the number of responses ranges from 30 to 202, with an average of about 101. In total, I run 409 times 20 regressions, where the former is the number of respondents and the latter is the number of variables.

Table 4.5 shows the results from these regressions. The results suggest that the determinants of *expret* indeed differ considerably across respondents. Columns 2–5 report the most relevant properties of the distribution of adjusted R^2 across respondents for each of the considered variables. Over all variables, adjusted R^2 statistics range from slightly negative to up to about 72%, suggesting that, for each variable, there exist respondents who do not consider the variable at all, while others assign a very high importance to it when forecasting the DAX. The variable with the highest average adjusted R^2 across respondents is *dax1to0*, which was also the variable that showed the highest overlap with survey and time fixed effects (see Chapter 4.5.2). The variable for which the importance varies the most across respondents is *conf*.

The last three columns of Table 4.5 document the heterogeneity of the correlation coefficients between the variables and *expret* across respondents. The way how the estimated coefficients are distributed between having a positive sign and having a negative sign provides insight into the idiosyncratic variation in *expret*. It is also informative about why some variables have a higher overlap with survey and time fixed effects than others.[8] In this analysis, I do not consider whether the coefficients are statistically significant or not, given that the focus is only the variance of *expret*.[9] The three columns reveal that the degree of heterogeneity of the correlation between each variable and *expret* across respondents is relatively high. One can distinguish between two groups of variables. In the first group, the estimated coefficients show the same sign for the large majority of the respondents. The variable with the highest agreement across respondents is *dax1to0*, for which I measure a negative relationship with *expret* for about 86% of respondents. Other examples are *ep* (26.65% positive vs. 73.35% negative) and *dax3to1* (27.63% positive vs. 72.37% negative). In the second group, the estimated coefficients are more or less evenly balanced be-

[8]The sign alone is of course not sufficient to explain the overlap of a variable with the common time-series variation in *expret*. The degree of overlap also depends on the average magnitude of the coefficients in both groups.

[9]When I consider statistical significance, I find that the correlations with *expret* are statistically insignificant at the 5% level for the majority of respondents and variables. This is also true when I restrict the sample to respondents with at least 100 observations or when I use a 10% threshold instead of the 5% threshold for statistical significance.

Table 4.5: Idiosyncratic variance of *expret*

Variable	N	Min R^2	Avg. R^2	Std. dev. R^2	Max R^2	Neg. coefficient (%)	Zero coefficient (%)	Pos. coefficient(%)
dax1to0	409	-0.0323	0.1011	0.1134	0.6004	86.06	0.00	13.94
dax12to3	409	-0.0336	0.0547	0.0946	0.5902	61.86	0.00	38.14
dax3to1	409	-0.0323	0.0514	0.0723	0.3528	27.63	0.00	72.37
dp	409	-0.0302	0.0945	0.1241	0.723	35.7	0.00	64.3
ep	409	-0.0346	0.0791	0.1333	0.6498	26.65	0.00	73.35
ipgrowth (shifted)	409	-0.0332	0.0466	0.0811	0.6019	47.68	0.00	52.32
conf (shifted)	409	-0.0339	0.0901	0.1175	0.5486	64.79	0.00	35.21
empl (shifted)	409	-0.0327	0.0504	0.0872	0.4834	57.46	0.00	42.54
oil	409	-0.0357	0.0253	0.0536	0.3054	60.39	0.00	39.61
exchrate	409	-0.0321	0.0468	0.0893	0.477	59.90	0.00	40.10
infl (shifted)	409	-0.0351	0.0374	0.0765	0.5178	54.28	0.00	45.72
expsit	409	-0.0336	0.023	0.0558	0.2963	32.52	0.24	67.24
sit	409	-0.0333	0.0178	0.0483	0.3068	52.57	0.00	47.43
expint_lt	409	-0.0332	0.0216	0.0588	0.4029	36.19	0.49	63.33
expinfl	409	-0.0334	0.0136	0.0518	0.4452	50.12	0.00	49.88
expint_st	409	-0.0336	0.0154	0.0483	0.341	56.72	0.24	43.03

This table illustrates the heterogeneity of the respondents' DAX expectations. The dependent variable *expret* has been orthogonalized with respect to the variable *corrected*. Columns 3–6 report characteristics of the distribution of adj. R^2 statistics from regressions of *expret* on the respective variables listed in the first column. Columns 7–9 show how coefficients on the respective variables are distributed across having a negative sign, being exactly zero or having a positive sign.

tween having a positive and having a negative sign. Examples are *infl* (54.28% positive vs 45.72% negative), which is also the variable with the lowest overlap with survey fixed effects (see Chapter 4.5.2) and *ipgrowth* (47.68% positive vs. 52.32% negative), which also ranks very low in Chapter 4.5.2.

4.6 Expected Returns And Economic Conditions

In this section, I explore whether my survey measures of stock return expectations are consistent with macro-financial theory and the empirical evidence based on realized returns. The predominant view in the macro-financial literature is that expected excess returns on stocks vary with economic conditions and are counter-cyclical, i.e. they are higher when economic conditions are bad and vice versa. This view goes back to Fama and French (1989), who, using data for the US economy between 1927 and 1987, document that variables that are considered to be positively correlated with subsequent realized returns, e.g. the dividend–price ratio, were high when economic conditions were bad and low when economic conditions were good.[10] In contradiction to this view, previous studies using US survey data have found that survey measures of stock return expectations are both positively correlated with proxies for expected returns (e.g. Vissing-Jorgensen, 2003; Greenwood and Shleifer, 2014; Amromin and Sharpe, 2014) and economic conditions (e.g. Amromin and Sharpe, 2014). Using a dataset which has not been used to study this question before, covers Germany instead of the US, combines stock market and macroeconomic expectations and features long, respondent-level time-series on a monthly frequency, I present more evidence on the relationship between stock market expectations and economic conditions.

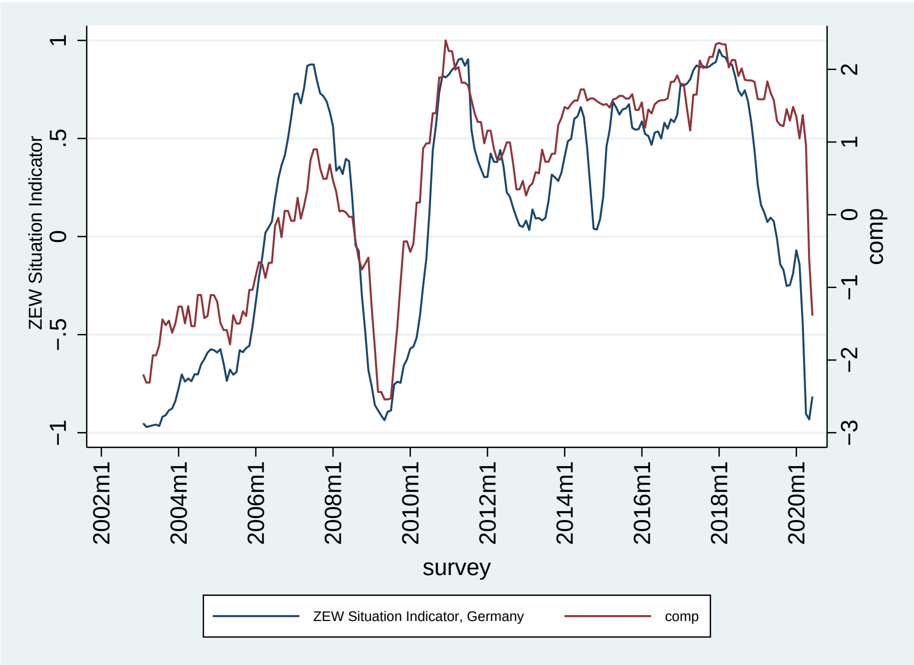
4.6.1 Measuring Economic Conditions

I use four different variables to measure economic conditions – two direct, economic measures and two indirect, financial measures. The first direct, economic measure is a composite economic indicator for Germany (*comp*). The composite indicator *comp* is the first principal component resulting from a principal component analysis of *ipgrowth*, *empl*, *conf* and *infl* (see Chapter 4.4.2). The first component explains about 43% of the variables' total variation and is positively correlated with all variables but *infl*. The use of a composite economic indicator simplifies my analysis because I have to consider only one variable that proxies for economic conditions instead of four. The second direct measure is the respondents' own subjective assessment of the current economic situation in Germany (*sit*, hereafter) from the ZEW FMS dataset. In the survey, the participants of the ZEW FMS are asked whether they think that the current economic situation in Germany is "good", "normal" or "bad". The variable thus already provides the respondents' subjective classifications of survey periods. Figure 4.5 compares the time-series of *comp* and the ZEW Situation Indicator Germany, where the latter is the difference between the share of respondents who assess

[10] A search of the literature has not yielded more recent empirical results on the relationship between expected excess returns on stocks and economic conditions.

the situation as "good" and the share of respondents who assess the situation as "bad". Interestingly, although there are short-term deviations, e.g. in the year 2015, both time-series broadly show the same cyclical pattern. The similarity between the two time-series suggests that the interpretation of the most recent economic data differs systematically between respondents. These differences, however, cancel out when the individual assessments of the current economic situation in Germany are aggregated in this way.

Figure 4.5: Comparison of the two direct measures of German economic conditions



Note: This figure compares the ZEW Situation Indicator and *comp*. The ZEW Situation Indicator is calculated as the difference between the shares of respondents who assess the current economic situation in Germany as "good" and who assess the current economic situation in Germany as "bad".

The indirect, financial measures are the log dividend–price ratio (*dp*) and the log earnings–price ratio (*ep*) of the CDAX, which are considered to be counter-cyclical in the literature (see e.g. Cochrane, 2017). As Figure 4.6 shows, this is only partially the case for Germany during the sample period. Figure 4.6a, which plots the deciles of *dp* against the respective averages of *comp* and the *ZEW Situation Indicator*, reveals that the relationship between *dp* and economic conditions is inversely U-shaped, i.e. both low and high dividend–price ratios occurred when the two direct measures of economic conditions were low. The inverse U-shape has important implications for the relationship between *dp* and *expret*, because if *expret* are indeed counter-cyclical, I will not be able to validate this with *dp*. As Figure 4.6b illustrates, the relationship between *ep* and my direct measures of economic conditions is less ambiguous. With exception of the first and last *ep*-deciles, the relationship can be described as linear and downward-sloping. The difference between both figures suggests that the payout ratios of the CDAX companies are unusually low or high relative to economic conditions during the sample period. Figure 4.7, which compares the time-series of *dp* and *ep*, confirms this, as it shows a disconnect between dividends and earnings before and to a smaller extent, during the financial crisis of 2007–2009. This disconnect coincides with the economic boom before the financial crisis, which generates the ambiguous relationship between *dp* and economic conditions. I will therefore choose *ep* over *dp* whenever I have to choose between the two measures.

4.6.2 Are Expected Returns Counter-cyclical?

If expected returns are counter-cyclical, I should be able to detect positive relationships between my survey measures of stock return expectations and *ep* and, to a lesser extent, *dp* and negative relationships between my survey measures of stock return expectations and *sit* and *comp*. To rule out that the regression results depend on the question format, I consider both available measures of DAX expectations, i.e. the quantitative forecast *expret* and the qualitative forecast *expdir*. An additional advantage of using the qualitative forecast is that the results are robust to large outliers in *expret*. In the analysis, I treat the qualitative forecast *expdir* as a continuous variable, which allows me to use the OLS estimator, facilitating the comparison between the results for both measures of DAX expectations. I also re-define *expdir* as

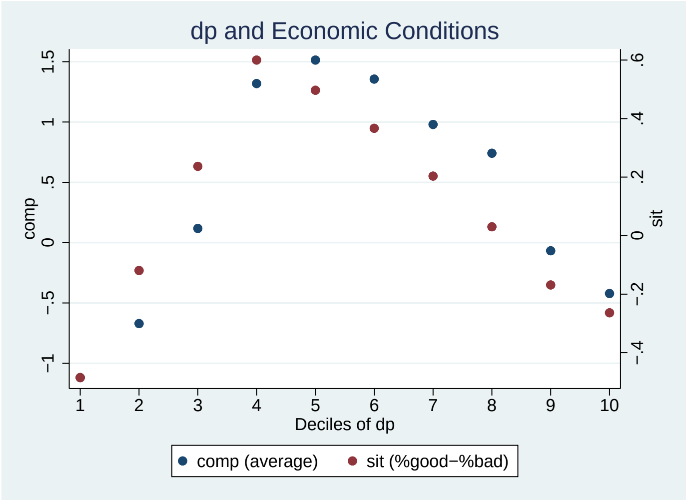
$$\widetilde{expdir}_{i,s,t} = \begin{cases} 1 & \text{if} \quad expdir_{i,s,t} = \text{“increase”} \\ 0 & \text{if} \quad expdir_{i,s,t} = \text{“not change”} \\ -1 & \text{if} \quad expdir_{i,s,t} = \text{“decrease”} \end{cases} . \tag{4.8}$$

To test my hypothesis of counter-cyclical stock return expectations, I run regressions of *expret* and *expdir* on my four different measures of economic conditions and control variables. As control variables, I include the respondents' own outlooks for the macroeconomy (*expsit*), inflation (*expinfl*), short-term (*expint_st*) and long-term interest rates (*expint_lt*), as well as the prior one-month return of the DAX (*dax1to0*). I control for the respondents' economic outlook, because Amromin and Sharpe (2014) have shown that it matters for stock market expectations. Moreover, Greenwood and Shleifer (2014) and Barberis et al. (2015) document that the recent returns of the equity market are positively correlated with survey stock market expectations.

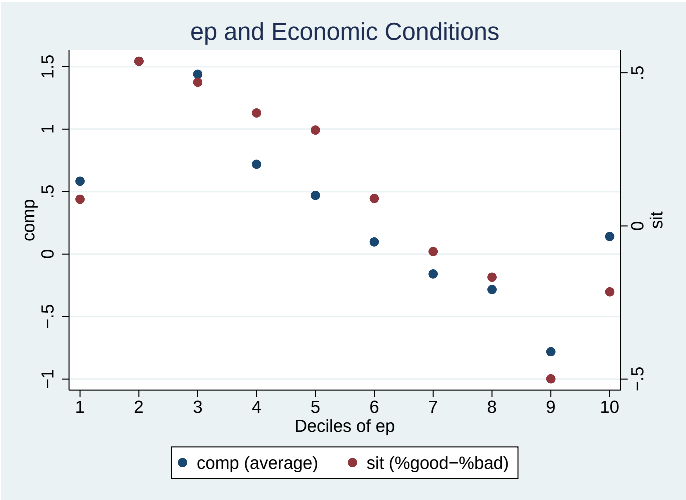
Tables 4.6 reports the regression results. The results are not unanimously in support of my hypothesis and, in some cases, reverse when I study *expdir* instead of *expret*. Consider, for example, the results for the regressions on *dp* documented in columns 1 and 2. Whereas the coefficient on *dp* in the regression of *expret* is positive (column 1), it is negative in the regression of *expdir* (column 2). The estimates of specifications 3–4 suggest that the contradictory relationship between *dp* and my two survey measures of stock return expectations might at least in part be an implication of the disconnect between dividends and earnings described in the previous section: consistent with my hypothesis, the coefficients on *ep* are both positive and also highly statistically significant.[11]

[11] If I restrict the sample to the years after 2010 (not shown), i.e. after dividends and earnings

Figure 4.6: The dividend–price ratio, the earnings–price ratio and economic conditions



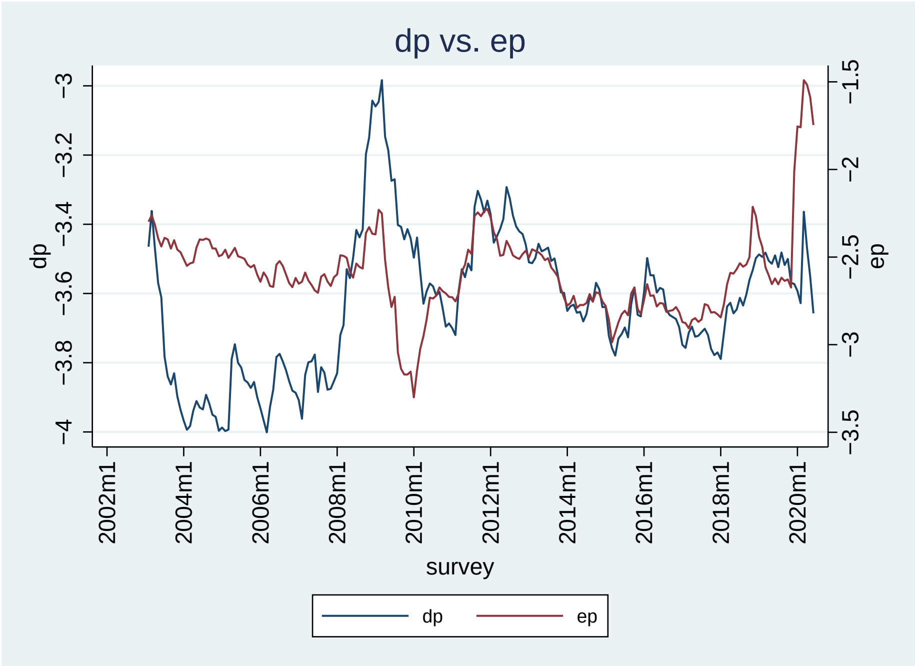
(a) *dp* and economic conditions



(b) *ep* and economic conditions

Note: This figure shows how the two indirect measures of economic conditions, *dp* and *ep*, are related to the two direct measures of economic conditions, *comp* and *sit*. Figure 4.6a plots the average of *comp* and an aggregated measure of *sit* against *dp*. The aggregated measure of *sit* is calculated as the difference between the shares of responses where *sit* = "good" and *sit* = "bad", respectively, i.e. the ZEW Situation Indicator. Figure 4.6b plots the average of *comp* and the aggregated measure of *sit* against *ep*.

Figure 4.7: Development of dividends and earnings of CDAX companies



Note: This figure compares the developments of *dp* and *ep* over time.

In contrast, the results for *sit*, documented in columns 5 and 6, are both not in support of my hypothesis. More specifically, I neither find that *expret* is on average higher when respondents assess the current situation as "bad" nor that the respondents are more likely to expect the DAX to increase (*expdir*). On the contrary, the respondents are actually less likely to expect the DAX to increase when they think the current economic situation is "bad" (column 6). Columns 7 and 8 reveal that *comp* shows the same contradictory pattern as *dp* and, to a lesser extent, *sit*. While *comp* is negatively associated with *expret* (column 7), which is in support of my hypothesis, its correlation with *expdir* is statistically insignificant (column 8), which is not in support of my hypothesis. The most supportive for my hypothesis of counter-cyclical stock market expectations are specifications 9 and 10, in which my survey measures of stock return expectations are regressed on all measures of economic conditions but *dp*.[12] Whereas *sit* is still negatively associated with return expectations, the coefficients on *ep* and *comp* are in line with my hypothesis, i.e. return expectations are on average negatively correlated with economic conditions.

have started to move together (see Figure 4.7), I find a positive but statistically insignificant coefficient in the equivalent of specification 2. This result gives additional support to my side-hypothesis that the contradictory results in specification 1–2 can be attributed to the disconnect between dividends and earnings.

[12] *dp* is highly correlated with *ep* and, based on my analysis in Chapter 4.6.1, an inferior measure of the valuation of the CDAX. The results from a test for multicollinearity suggest that it is unproblematic to include the remaining three measures of economic conditions simultaneously: variance inflation factors range from 1.31 (*ep*) to 3.39 (*sit*).

Table 4.6: Are expected returns counter-cyclical?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	expret	*expdir*	*expret*	*expdir*	*expret*	*expdir*	*expret*	*expdir*	*expret*	*expdir*
dp	0.0037***	-0.0425***								
	(0.0012)	(0.0088)								
ep			0.0074***	0.0346***					0.0071***	0.0412***
			(0.0006)	(0.0058)					(0.0006)	(0.0057)
sit = normal					-0.0018	-0.0418***			-0.0078***	-0.0763***
					(0.0012)	(0.0119)			(0.0013)	(0.0127)
sit = bad					0.0026	-0.1070***			-0.0138***	-0.2021***
					(0.0024)	(0.0197)			(0.0023)	(0.0205)
comp							-0.0057***	0.0006	-0.0078***	-0.0449***
							(0.0012)	(0.0099)	(0.0013)	(0.0114)
expsit = not change	-0.0170***	-0.1890***	-0.0167***	-0.1888***	-0.0165***	-0.2110***	-0.0148***	-0.1898***	-0.0167***	-0.2120***
	(0.0015)	(0.0133)	(0.0015)	(0.0133)	(0.0016)	(0.0132)	(0.0015)	(0.0131)	(0.0015)	(0.0129)
expsit = worsen	-0.0476***	-0.5255***	-0.0479***	-0.5481***	-0.0454***	-0.5694***	-0.0434***	-0.5407***	-0.0475***	-0.5815***
	(0.0027)	(0.0247)	(0.0027)	(0.0253)	(0.0028)	(0.0253)	(0.0027)	(0.0254)	(0.0028)	(0.0253)
expinfl = not change	0.0023**	0.0159	0.0002	0.0038	0.0024**	0.0251**	0.0011	0.0146	-0.0001	0.0106
	(0.0012)	(0.0108)	(0.0012)	(0.0107)	(0.0012)	(0.0107)	(0.0012)	(0.0106)	(0.0012)	(0.0105)
expinfl = decrease	0.0056***	0.0362*	0.0019	-0.0025	0.0066***	0.0391**	0.0044**	0.0212	0.0010	0.0068
	(0.0021)	(0.0203)	(0.0020)	(0.0191)	(0.0021)	(0.0190)	(0.0020)	(0.0188)	(0.0020)	(0.0186)
expint_st = not change	0.0035***	0.0042	0.0046***	-0.0136	0.0047***	-0.0031	0.0056***	-0.0121	0.0067***	0.0084
	(0.0013)	(0.0124)	(0.0013)	(0.0128)	(0.0013)	(0.0130)	(0.0013)	(0.0126)	(0.0013)	(0.0123)
expint_st = decrease	0.0144***	0.0424**	0.0151***	-0.0207	0.0179***	0.0195	0.0165***	-0.0046	0.0156***	0.0063
	(0.0022)	(0.0177)	(0.0024)	(0.0183)	(0.0022)	(0.0181)	(0.0022)	(0.0183)	(0.0022)	(0.0180)
expint_lt = not change	-0.0076***	-0.0859***	-0.0077***	-0.0853***	-0.0075***	-0.0860***	-0.0076***	-0.0854***	-0.0075***	-0.0859***
	(0.0012)	(0.0110)	(0.0012)	(0.0110)	(0.0012)	(0.0111)	(0.0012)	(0.0111)	(0.0012)	(0.0110)
expint_lt = decrease	-0.0278***	-0.2354***	-0.0270***	-0.2256***	-0.0282***	-0.2282***	-0.0286***	-0.2312***	-0.0272***	-0.2224***
	(0.0028)	(0.0224)	(0.0027)	(0.0219)	(0.0028)	(0.0223)	(0.0028)	(0.0224)	(0.0027)	(0.0219)
dax1to0	-0.0181***	-0.0479***	-0.0176***	-0.0361***	-0.0188***	-0.0402***	-0.0190***	-0.0412***	-0.0179***	-0.0354***
	(0.0006)	(0.0045)	(0.0006)	(0.0046)	(0.0006)	(0.0046)	(0.0006)	(0.0046)	(0.0006)	(0.0047)
corrected	-0.0149***		-0.0141***		-0.0151***		-0.0139***		-0.0137***	
	(0.0033)		(0.0033)		(0.0033)		(0.0033)		(0.0033)	
Constant	0.0425***	0.6129***	0.0431***	0.6473***	0.0405***	0.6785***	0.0399***	0.6352***	0.0486***	0.7254***
	(0.0016)	(0.0145)	(0.0016)	(0.0148)	(0.0020)	(0.0164)	(0.0016)	(0.0143)	(0.0020)	(0.0177)
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	44,311	44,311	44,311	44,311	44,311	44,311	44,311	44,311	44311	44311
R^2	0.1107	0.0893	0.1178	0.0888	0.1095	0.0894	0.1131	0.0864	0.1225	0.0948
Adj. R^2	0.1105	0.0891	0.1176	0.0886	0.1092	0.0891	0.1128	0.0862	0.1222	0.0946

Note: This table documents the results of regressions of *expret* and *expdir* on measures of economic conditions and control variables. All dependent variables were standardized. Standard errors were clustered on the respondent-level and are reported in parantheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

To sum up, when I study *expret*, the results are largely in support of my hypothesis that stock market expectations are counter-cyclical. For three out of the four measures of economic conditions studied, return expectations are on average higher when economic conditions are lower. The one exception is the respondents' own assessment of current economic conditions, which is the only subjective measure of economic conditions considered in the analysis. In contrast, when I study *expdir*, I find that economic conditions are either unrelated or even positively associated with stock market expectations. The discrepancies between the results for *expret* and *expdir*, however, vanish when all measures of economic conditions are considered together.

The results for *expret* and to a limited extent for *expdir*, differ from central findings of the previous literature on survey measures of stock market expectations. In contrast to Greenwood and Shleifer (2014) and Amromin and Sharpe (2014), I find that the valuation of the stock market, proxied by *dp* and *ep*, is on average positively associated with the DAX return expectations of the survey respondents. Moreover, in contrast to Greenwood and Shleifer (2014), Amromin and Sharpe (2014) and Barberis et al. (2015), I do not find evidence for an extrapolation of past returns. Both survey measures of DAX return expectations are negatively correlated with the DAX return over the previous month in all specifications.

Why are the results for *expret* and *expdir* qualitatively different in some cases? There are three possible explanations. First, the qualitative differences might arise because the respondents give answers to the question asking for a point forecast of the DAX (i.e. *expret*) that contradict their answers to the question asking for a directional forecast of the DAX (i.e. *expret*). Second, outliers in *expret* might impact the estimates such that the direction of the measured relationship between economic conditions and *expret* differs from that of the respective relationship with *expdir*. Finally, the qualitative differences might be the result of the different scales of the two survey measures of DAX expectations, i.e. metric for *expret* and ordinal for *expdir*.

I first turn to inconsistent answers. Table 4.7 reports features of the distributions of *expret* conditional on *expdir*. These statistics suggest that the respondents' quantitative forecasts are largely consistent with their respective qualitative forecasts.[13] More specifically, *expret* is on average positive, close to zero and negative, if respondents answer "increase", "not change" and "decrease", respectively. However, there are also a few inconsistent answers. For example, the smallest value for *expret* in the category "increase" is -91%, which, in addition to having the "wrong" sign, is also very large in magnitude. To quantify the extent to which inconsistent answers are responsible for the differences between the results for the qualitative and quantitative forecasts, I drop all inconsistent answers and re-run my regressions of both survey measures of DAX return expectations on my measures of economic conditions. I also drop all observations in the category "not change", given that there are no observations for which *expret* is exactly 0. Table 4.8 reports the results from these regressions. Although the exclusion of inconsistent answers produces stronger results, i.e. coefficients of variables that are hypothesized to be positively associated with DAX expectations become larger and vice versa, it does not solve the problem

[13]The order of the questions in the questionnaire is the following: First qualitative, then quantitative.

Table 4.7: Distributions of *expret* conditional on *expdir*

expdir	Min	p10	p25	p50	Mean	p75	p90	Max
"increase"	-91.07	1.47	3.33	5.78	7.01	9.32	14.20	80.97
"not change"	41.80	-3.79	-1.47	0.22	0.29	2.05	4.43	41.30
"decrease"	-87.64	-16.16	-11.07	-7.32	-8.35	-4.41	-2.18	47.47

Note: This table reports characteristics of the conditional distributions of *expret* (in percent), conditional on *expdir*. The labels p10, p25, p50, p75 and p90 refer to the 10th, 25th, 50th, 75th and 90th percentile of the overall distribution of *expret*.

of contradicting results in regressions of *expret* vs. *expdir*. In particular, the coefficient on *dp* is still positive in specification (1) and negative in specification (2) and the coefficient on *comp* is still negative in specification (7) and positive but statistically insignificant in specification (8).

I next turn to the role of outliers in *expret*. To quantify the effect that outliers have on my estimates, I re-run all regression with a winsorized version of *expret*. The winsorization is done by replacing the 5% smallest and the 5% largest values of *expret* by the variable's 5th and 95th percentile, respectively, where both percentiles are calculated from the distributions of *expret* specific to each survey wave. Table 4.9 documents the regression results. Again, the coefficient on *dp* is positive in specification (1) but negative in specification (2) and the coefficient on *comp* is negative in specification (7) and positive but statistically insignificant in specification (8). Thus, outliers in *expret* are not the reason for why the results are qualitatively different.

Having ruled out both inconsistent responses and outliers as the causes of the qualitative differences between the results for *expret* and *expdir*, the only remaining explanation is that the differences are due to the different scales of the two variables. Given that the respondents can only choose between "increase", "not change" and "decrease" when answering the question asking for a directional DAX forecast and that they are able to provide an exact forecast in the question asking for a point forecast, *expdir* co-varies less with perceived economic conditions than *expret* by construction.

4.6.3 Expected Returns, Economic Conditions And The Respondents' Personal Characteristics

I now turn to the relationship between the respondents' personal characteristics and their DAX expectations, which I have ignored so far. As summarized in the literature overview, the empirical evidence suggests that the individual characteristics of respondents matter for their expectations. The focus of my analysis is whether the respondents' characteristics affect the relationships between *expret* and economic conditions and, if this is the case, whether these characteristics are associated with pro-cyclical or counter-cyclical DAX expectations. Differences in personal characteristics might thus explain why the correlations between economic conditions and *expret* vary extensively across respondents (see Chapter 4.5.3).

I study how the relationship between *expret* and economic conditions depends on the following characteristics: age and age cohort, indicators of the

Table 4.8: The effect of inconsistent answers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	expret	*expdir*	*expret*	*expdir*	*expret*	*expdir*	*expret*	*expdir*	*expret*	*expdir*
dp	0.0039**	-0.0429***								
	(0.0015)	(0.0112)								
ep			0.0090***	0.0429***					0.0085***	0.0514***
			(0.0008)	(0.0078)					(0.0009)	(0.0076)
sit = normal					-0.0015	-0.0320**			-0.0085***	-0.0640***
					(0.0016)	(0.0147)			(0.0017)	(0.0162)
sit = bad					0.0036	-0.1223***			-0.0154***	-0.2072***
					(0.0031)	(0.0247)			(0.0030)	(0.0272)
comp							-0.0067***	0.0103	-0.0090***	-0.0358**
							(0.0015)	(0.0122)	(0.0016)	(0.0141)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	30,442	30,442	30,442	30,442	30,442	30,442	30,442	30,442	30,442	30,442
R^2	0.1272	0.1058	0.1366	0.1064	0.1261	0.1069	0.1304	0.1033	0.1417	0.1129
Adj. R^2	0.1269	0.1055	0.1363	0.1061	0.1257	0.1066	0.1302	0.1030	0.1414	0.1125

Note: This table documents the results of regressions of *expret* and *expdir* on measures of economic conditions and control variables. All observations for which respondents have provided quantitative and qualitative DAX forecasts which are inconsistent with each other were dropped from the regression. Observations were classified as inconsistent if *expret* < 0 and *expdir* = "increase" or *expret* > 0 and *expdir* = "decrease". Also, all observations, for which *expdir* = "not change", were dropped from the regression. Control variables are *expsit*, *expinfl*, *expint_st*, *expint_lt* and *dax1to0*. All independent variables were standardized. Standard errors were clustered on the respondent-level and are reported in parantheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

Table 4.9: The effect of outliers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	expret	*expdir*	*expret*	*expdir*	*expret*	*expdir*	*expret*	*expdir*	*expret*	*expdir*
dp	0.0030***	-0.0425***								
	(0.0010)	(0.0088)								
ep			0.0072***	0.0346***					0.0068***	0.0412***
			(0.0006)	(0.0058)					(0.0006)	(0.0057)
sit = normal					-0.0013	-0.0418***			-0.0069***	-0.0763***
					(0.0010)	(0.0119)			(0.0011)	(0.0127)
sit = bad					0.0037*	-0.1070***			-0.0118***	-0.2020***
					(0.0021)	(0.0197)			(0.0019)	(0.0205)
comp							-0.0057***	0.0006	-0.0073***	-0.0449***
							(0.0010)	(0.0099)	(0.0011)	(0.0114)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	44,311	44,311	44,311	44,311	44,311	44,311	44,311	44,311	44,311	44,311
R^2	0.1254	0.0893	0.1347	0.0888	0.1247	0.0894	0.1292	0.0864	0.1400	0.0948
Adj. R^2	0.1252	0.0891	0.1345	0.0886	0.1245	0.0891	0.1289	0.0862	0.1398	0.0946

Note: This table documents the results of regressions of *expret* and *expdir* on measures of economic conditions and control variables. The variable *expret* was winsorized by replacing the 5% smallest and the 5% largest values of *expret* by its 5th and 95th percentiles, respectively. Control variables are *expsit*, *expinfl*, *expint_st*, *expint_lt* and *dax1to0*. All independent variables were standardized. Standard errors were clustered on the respondent-level and are reported in parantheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

levels of expertise in conducting DAX forecasts and main occupation.[14] I restrict my analysis to *expret*, because the results presented in the previous section suggest that it is a more precise measure of the respondents' DAX expectations than *expdir*. Moreover, because these specifications did not show contradictory results and to save space, I report only the results of the regressions in which all measures of economic conditions are included simultaneously (the equivalents of specifications 9 and 10 in Table 4.6).

Table 4.10 documents how the relationships between *expret* and *ep*, *comp* and *sit* vary with the respondents' age and their age cohorts. For a reduced complexity of the analysis, I have divided the group of respondents who provided their birth date into four groups along the distribution of the respondents' birth years. The breakpoints for the four age cohorts are the three quartiles of the distribution of birth years. The distribution of birth years ranges from 1938 to 1990 and the three quartiles are 1958, 1963 and 1969. Column 2 (specification 1) of Table 4.10 reveals that the results for the relationships between *expret* and the three measures of economic conditions documented in Table 4.6 also hold in the sub-sample, for which the birth years of the respondents are available. Interestingly, when I include *age* into the model (column 3), which is negatively associated with *expret*, the relationships between *expret* and *ep* and *sit* remain largely unchanged, whereas the coefficient on *comp* loses its statistical significance. The most likely explanation for the latter finding is that *comp* and age are spuriously correlated in the sample, i.e. the upward movement of the distribution of age (see Figure 4.2d) during the sample period happens to coincide with an upward trend in economic conditions as measured by *comp* (see Figure 4.5).[15] Column 4 (specification 3) reports the result of the regression, in which I interact my three measures of economic conditions with *age*. The estimated model suggests that the relationship between *expret* and *ep* depends on age, while those of *comp* and *sit* do not. More specifically, the coefficient on *ep* decreases when age increases. As can be seen from Figure 4.8, which plots the coefficient on *ep* against age, the estimated model implies that the association between *ep* and *expret* is positive (i.e. counter-cyclical) if age is below 69 and statistically insignificant if age is 69 or higher (judged by a 95% confidence interval). Given that only a small minority of the financial market experts in the sample has reached the age of 69, this threshold holds no economic significance. Finally, when I interact the three measures of economic conditions with the respondents' age cohorts (column 5), I do not find any differences across age cohorts.

I next explore whether the relationships between *expret* and *ep*, *comp* and *sit* depend on the respondents' level of expertise in conducting DAX forecasts. There are four self-reported measures of expertise available to me. These are the respondents' own assessments of their levels of expertise in the areas of stock forecasts in general, in conducting DAX point and interval forecasts and in assessing the fundamental value of the DAX, as well as the respondents' professional experience in conducting DAX forecasts, i.e. whether and how

[14] I do not consider the career entry year or the number of years of working experience, because these variables are highly correlated with age – the coefficient of correlation is 0.9 – and thus imply very similar results.

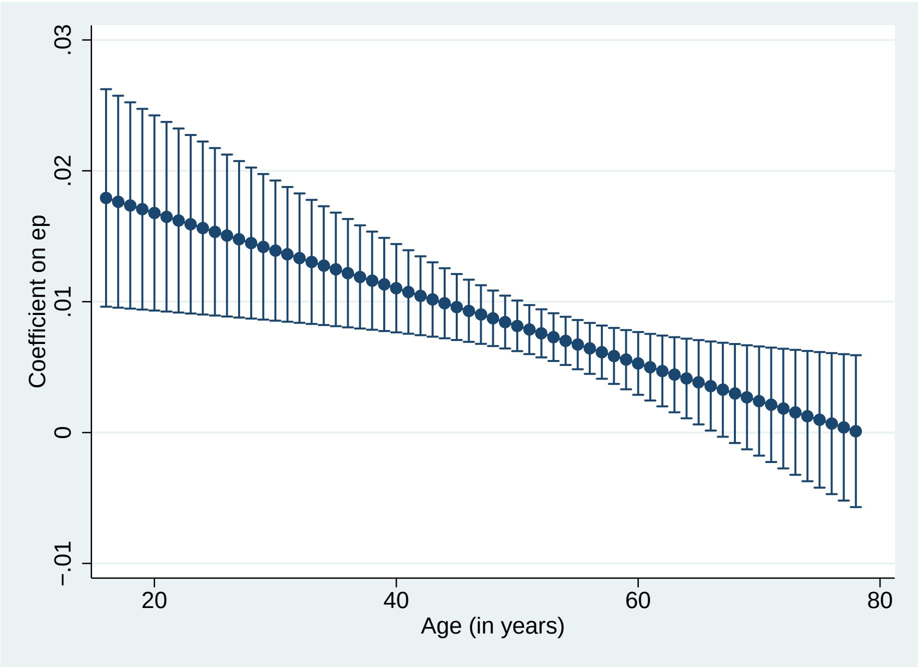
[15] While *comp* seems to follow an upward trend during the sample period, its components are all stationary variables. Hence, detrending *comp* to remove the spurious correlation between it and age would be inappropriate.

Table 4.10: Expected returns, economic conditions and age

	(1)	(2)	(3)	(4)
	expret	*expret*	*expret*	*expret*
ep	0.0070***	0.0080***	0.0225***	0.0088***
	(0.0009)	(0.0009)	(0.0060)	(0.0022)
ep × age			-0.0003**	
			(0.0001)	
ep × cohort = 2				-0.0004
				(0.0029)
ep × cohort = 3				-0.0021
				(0.0031)
ep × cohort = 4				-0.0044
				(0.0029)
comp	-0.0075***	0.0011	-0.0112	-0.0066*
	(0.0015)	(0.0018)	(0.0083)	(0.0033)
comp × Age			0.0003	
			(0.0002)	
comp × Cohort = 2				-0.0015
				(0.0042)
comp × Cohort = 3				-0.0013
				(0.0050)
comp × Cohort = 4				-0.0005
				(0.0038)
sit = good × Cohort = 2				0.0112
				(0.0074)
sit = good × Cohort = 3				0.0116
				(0.0076)
sit = good × Cohort = 4				0.0081
				(0.0083)
sit = normal	-0.0067***	-0.0050***	-0.0160*	-0.0036
	(0.0016)	(0.0016)	(0.0085)	(0.0025)
sit = normal × Age			0.0002	
			(0.0002)	
sit = normal × Cohort = 2				0.0084
				(0.0067)
sit = normal × Cohort = 3				0.0052
				(0.0070)
sit = normal × Cohort = 4				0.0055
				(0.0072)
sit = bad	-0.0101***	-0.0060**	-0.0138	-0.0023
	(0.0028)	(0.0029)	(0.0163)	(0.0057)
sit = bad × age			0.0002	
			(0.0003)	
Age		-0.0022***	-0.0021***	
		(0.0004)	(0.0004)	
Constant	0.0475***	0.1402***	0.1366***	0.0397***
	(0.0024)	(0.0176)	(0.0199)	(0.0055)
Controls	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes
N	24,611	24,611	24,611	24,611
R^2	0.1275	0.1341	0.1361	0.1285
Adj. R^2	0.1270	0.1336	0.1354	0.1276

Note: This table reports the results of regressions of *expret* on measures of economic conditions, the respondents' age and their age cohort. Control variables are *expsit*, *expinfl*, *expint_st*, *expint_lt* and *dax1to0*. All independent variables were standardized. Standard errors were clustered on the respondent-level and are reported in parantheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

Figure 4.8: The coefficient on *ep* conditional on age



Note: This figure shows how the measured relationship between *expret* and *ep* depends on the respondents' age. The plot is based on the regression results documented in Table 4.10 and shows the estimates of the coefficient on *ep* and the accompanying 95% confidence intervals.

often respondents have conducted DAX forecasts outside of the context of the ZEW FMS before.

A natural hypothesis is that a high level of expertise is associated with counter-cyclical DAX expectations. Experts should know that subsequent realized returns are on average higher when economic conditions are bad, given that this is well documented in the literature. Moreover, I also test whether taking an interest in the results of the ZEW FMS on stock markets in general matters for the respondents' DAX expectations conditional on economic conditions. Respondents who take interest in stock market forecasts might, for example, put more effort in making their own forecasts than those who are not.

Tables 4.11 and 4.12 report the regression results. The results on the interactions between my measures of expertise and my measures of economic conditions do not suggest that a higher level of expertise is associated with more counter-cyclical DAX expectations: the interactions between expertise and economic conditions in specifications (1)–(3) reported in Table 4.11 as well as the interactions between professional forecasting activities and economic conditions reported in specification (2) in Table 4.12 all are statistically not significant. When I differentiate by whether a respondent takes interest in the results of the ZEW FMS on stock markets in general, I find that the coefficient on *comp* is only statistically significant (i.e. counter-cyclical) if the respondents report that they are interested.

Lastly, I differentiate by the respondents' self-reported main occupation. Table 4.13 reports the regression results for each of the ten categories. While not all are statistically significant, the coefficients on *ep* and *comp* across all main occupations have the same sign and also the same sign as the respective coefficients from the main regression reported in Table 4.6. With two exceptions, i.e. specifications 5 and 9, this is also the case for *sit*. Financial market experts with different main occupations thus mainly seem to differ with respect to whether they consider a given measure of economic conditions when forecasting the DAX or not. The results suggest that, of all the characteristics explored in this section, main occupation is the best differentiator when it comes to the relationship between DAX return expectations and measures of economic conditions.

4.7 Evaluating Forecasting Performance

In this section, I evaluate the forecast performance of the respondents to the ZEW FMS. I am interested in two characteristics of the respondents' DAX forecasts. First, I explore whether their forecasts are predictive for subsequent realized returns and, if this is the case, whether the forecasts are positively or negatively correlated with them. The sign of the correlation is of particular interest, given that Greenwood and Shleifer (2014) find that their survey measures of expected stock returns are negatively correlated with subsequent realized returns. They explain this puzzling finding with their result that proxies for expected excess stock returns and their survey measures of expected returns are negatively correlated. As I document relationships between *expret* and proxies for expected stock returns (e.g. the dividend–price ratio) that differ from those reported in Greenwood and Shleifer (2014), I expect to find that my survey measures of stock return expectations are positively correlated with subsequent realized returns. Second, I test whether the respondents' DAX fore-

Table 4.11: Expected returns, economic conditions, stock market expertise and taking interest in ZEW FMS results on stock markets

Dependent variable: *expret*	(1) Expertise: stocks	(2) Expertise: quantitative DAX forecasts	(3) Expertise: current valuation DAX	(4) Interest: stocks
ep	0.0095**	0.0076***	0.0099***	0.0077***
	(0.0041)	(0.0021)	(0.0029)	(0.0025)
ep × expertise = medium	-0.0014	0.0002	-0.0048	
	(0.0045)	(0.0026)	(0.0034)	
ep × expertise = high	-0.0041	-0.0042	-0.0029	
	(0.0044)	(0.0030)	(0.0033)	
ep × interested = yes				-0.0012
				(0.0028)
comp	-0.0052*	-0.0073**	-0.0064	-0.0039
	(0.0028)	(0.0031)	(0.0046)	(0.0024)
comp × expertise = medium	-0.0031	-0.0028	0.0000	
	(0.0040)	(0.0037)	(0.0051)	
comp × expertise = high	-0.0048	-0.0050	-0.0080	
	(0.0034)	(0.0054)	(0.0054)	
comp × interested = yes				-0.0076**
				(0.0031)
sit = good × expertise = medium	0.0115	0.0028	-0.0124	
	(0.0099)	(0.0079)	(0.0089)	
sit = good × expertise = high	-0.0084	-0.0115	-0.0087	
	(0.0085)	(0.0101)	(0.0087)	
sit = good × × interested = yes				-0.0085
				(0.0105)
sit = normal	-0.0085	-0.0142***	-0.0141*	-0.0097***
	(0.0065)	(0.0050)	(0.0079)	(0.0026)
sit = normal × expertise = medium	0.0087	0.0102	-0.0040	
	(0.0077)	(0.0071)	(0.0076)	
sit = normal × expertise = high	-0.0064	-0.0020	-0.0037	
	(0.0060)	(0.0099)	(0.0079)	
sit = normal × interested = yes				-0.0076
				(0.0093)
sit = bad	-0.0129*	-0.0138**	-0.0218***	-0.0181*
	(0.0075)	(0.0060)	(0.0069)	(0.0096)
Constant	0.0504***	0.0523***	0.0594***	0.0556***
	(0.0078)	(0.0066)	(0.0082)	(0.0086)
Controls	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes
N	16,342	16,536	16,536	14,517
R^2	0.1400	0.1423	0.1433	0.1405
Adj. R^2	0.1388	0.1412	0.1421	0.1394

Note: This table reports the results of regressions of *expret* on measures of economic conditions, three indicators of the respondents' level of expertise in conducting stock market forecasts and an indicator of whether the respondents take interest in the results of the ZEW FMS on stock markets. The labels "stocks", "quantitative DAX forecasts" and "current valuation DAX" refer to the respondents' levels of expertise in the areas of stock market forecasting in general, of making quantitative DAX forecasts and of DAX valuation, respectively. The expertise variables can take the values "low", "medium" and "high". The variable that indicates whether the respondents take interest in the results on stock markets can take the values "yes" or "no". Control variables are *expsit*, *expinfl*, *expint_st*, *expint_lt* and *dax1to0*. All independent variables were standardized. Standard errors were clustered on the respondent-level and are reported in parantheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

Table 4.12: Expected returns, economic conditions and professional experience in conducting DAX forecasts

	(1) *expret*	(2) *expret*
ep	0.0067***	0.0067***
	(0.0008)	(0.0014)
ep × DAX forecasts = sometimes		0.0034
		(0.0023)
ep × DAX forecasts = never		-0.0013
		(0.0018)
comp	-0.0082***	-0.0101***
	(0.0014)	(0.0024)
comp × DAX forecasts = sometimes		0.0055
		(0.0039)
comp × DAX forecasts = never		0.0022
		(0.0031)
Economic situation Germany = good × DAX forecasts = sometimes		0.0040
		(0.0063)
Economic situation Germany = good × DAX forecasts = never		-0.0035
		(0.0058)
Economic situation Germany = normal	-0.0078***	-0.0078***
	(0.0015)	(0.0020)
Economic situation Germany = normal × DAX forecasts = sometimes		0.0025
		(0.0067)
Economic situation Germany = normal × DAX forecasts = never		-0.0034
		(0.0052)
Economic situation Germany = bad	-0.0136***	-0.0143***
	(0.0026)	(0.0041)
Constant	0.0482***	0.0493***
	(0.0026)	(0.0040)
Controls	Yes	Yes
Person FE	Yes	Yes
N	30,765	30,765
R^2	0.1299	0.1312
Adj. R^2	0.1295	0.1306

Note: This table reports the results of regressions of *expret* on measures of economic conditions and an indicator of the respondents' professional experience in conducting DAX forecasts, *DAX forecasts*. The variable *DAX forecasts* can take the values "regular", "sometimes" and "never". Control variables are *expsit*, *expinfl*, *expint_st*, *expint_lt* and *dax1to0*. All independent variables were standardized. Standard errors were clustered on the respondent-level and are reported in parantheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

Table 4.13: Expected returns, economic conditions and the respondents' main occupation

Dependent variable: *expret*	(1) Economic research	(2) Trading	(3) Financing	(4) Management	(5) Security research	(6) Fund/portfolio management	(7) Investment advice	(8) Wealth management	(9) Risk management	(10) Other
ep	0.0070***	0.0044**	0.0073***	0.0032	0.0055**	0.0056***	0.0045***	0.0056***	0.0057**	0.0073**
	(0.0017)	(0.0019)	(0.0018)	(0.0019)	(0.0024)	(0.0013)	(0.0015)	(0.0015)	(0.0023)	(0.0027)
comp	-0.0069	-0.0059	-0.0098**	-0.0070**	-0.0012	-0.0064*	-0.0065**	-0.0069	-0.0051*	-0.0112*
	(0.0050)	(0.0050)	(0.0037)	(0.0028)	(0.0058)	(0.0033)	(0.0031)	(0.0042)	(0.0024)	(0.0057)
sit = normal	-0.0038	-0.0057	-0.0078*	-0.0054	-0.0023	-0.0036	-0.0134***	-0.0050	-0.0080**	-0.0052
	(0.0034)	(0.0040)	(0.0044)	(0.0042)	(0.0048)	(0.0033)	(0.0037)	(0.0042)	(0.0038)	(0.0063)
sit = bad	-0.0104	-0.0154*	-0.0219***	-0.0098	0.0021	-0.0067	-0.0061	-0.0095	0.0035	-0.0133
	(0.0065)	(0.0082)	(0.0065)	(0.0074)	(0.0050)	(0.0046)	(0.0086)	(0.0061)	(0.0059)	(0.0128)
Constant	0.0453***	0.0489***	0.0498***	0.0431***	0.0482***	0.0448***	0.0464***	0.0504***	0.0373***	0.0633***
	(0.0063)	(0.0083)	(0.0066)	(0.0083)	(0.0057)	(0.0043)	(0.0049)	(0.0056)	(0.0057)	(0.0148)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,309	2,636	3,236	5,047	3,206	7,775	4,403	4,867	2,549	2,652
R^2	0.1429	0.1073	0.1714	0.1046	0.1286	0.1484	0.1523	0.1633	0.2110	0.1054
Adj. R^2	0.1401	0.1026	0.1678	0.1021	0.1247	0.1468	0.1496	0.1609	0.2067	0.1007

Note: This table reports the results of regressions of *expret* on measures of economic conditions, conditional on the respondents' main occupation. Control variables are *expsit*, *expinfl*, *expint_st*, *expint_lt* and *dax1to0*. All independent variables were standardized. Standard errors were clustered on the respondent-level and are reported in parantheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

casts are more accurate than the historical average realized return, the latter being an often used benchmark which stock market forecasts are compared to in the literature (see e.g. Welch and Goyal, 2008).

I begin by studying the predictive power of aggregated versions of my two survey measures of DAX return expectations. These are an equally-weighted average of *expret* and the bull-bear spread, the latter being the difference between the shares of respondents who expect the DAX to increase and decrease, respectively, over the course of the next six months. I then explore whether there are differences in forecast performance between subgroups formed by the various personal characteristics available to me.

4.7.1 Aggregated Forecasts

To evaluate the predictive power of the aggregated return forecasts, I run separate regressions of an aggregated measure of realized six-month DAX returns on the average of *expret* and on the bull-bear spread. The regression model is

$$\bar{r}_s^{DAX,Q} = \alpha + \beta f_s^Q + \epsilon_s, \tag{4.9}$$

where $\bar{r}_s^{DAX,Q}$ is the aggregated measure of realized six-month DAX returns for survey wave s and f_s^Q is either the bull-bear spread ($bullbear_s$) or the average of *expret* ($quant_s$) in survey wave s. As the index $Q \in \{bullbear, quant\}$ indicates, $\bar{r}_s^{DAX,Q}$ depends on whether I study *bullbear* or *quant*. More specifically, I define the aggregated realized return $\bar{r}_s^{DAX,Q}$ as

$$\bar{r}_s^{DAX,Q} = (N_s)^{-1} \sum_{i=1}^{N_s} D_{i,s,t}^Q r_{s,t;t+6m}^{DAX}, \tag{4.10}$$

where N_s is the number of respondents in survey wave s, i indexes the respondents of survey wave s, $r_{s,t;t+6m}^{DAX}$ is the realized six-month DAX return associated with a DAX forecast made on survey day t during survey wave s and $D_{i,s,t}^Q$ is an indicator variable which takes the value of 1 if respondent i provided a forecast for forecast Q on survey day t during survey wave s and 0 otherwise. By only considering the realized returns specific to respondents who actually provided forecasts, I ensure that the aggregated measure of realized returns better aligns with the aggregated forecasts. The aggregated forecasts are calculated as

$$bullbear_s = (N_s)^{-1} \sum_{i=1}^{N_s} D_{i,s,t}^Q \widetilde{expdir}_{i,s,t} \tag{4.11}$$

and

$$quant_s = (N_s)^{-1} \sum_{i=1}^{N_s} D_{i,s,t}^Q expret_{i,s,t}, \tag{4.12}$$

respectively, where $\widetilde{expdir}_{i,s,t}$ is the continuous version of the directional DAX forecast defined in Equation (4.8).

Table 4.14 reports the regression results. I first regress $\bar{r}^{DAX,Q}$ on *bullbear*. I do this both for the whole time-series starting in 1991 (specification (1)), as well as the period starting in 2003 (specification (2)), which is the period for which *quant* is available. Realized six-month DAX returns are available

Table 4.14: Evaluating predictive power

	(1) $\bar{r}^{DAX,bullbear}$	(2) $\bar{r}^{DAX,bullbear}$	(3) $\bar{r}^{DAX,quant}$
bullbear	-0.0406	0.1618	
	(0.1161)	(0.1049)	
quant			1.3422**
			(0.6085)
Constant	0.0650	-0.0116	0.0182
	(0.0503)	(0.0489)	(0.0212)
N	338	205	205
R^2	0.0017	0.0340	0.0676
Adj. R^2	-0.0012	0.0292	0.0630

Note: This table documents the results of regressions of average realized six-month DAX returns, $\bar{r}_s^{DAX,Q}$, $Q \in \{bullbear, quant\}$, on the two aggregated DAX forecasts *bullbear* and *quant*. Specification (1) is estimated on the full sample, i.e. December 1991–June 2020, whereas specifications (2) and (3) are estimated on the sample, for which *quant* is available, i.e. February 2003–June 2020. Newey–West standard errors in parantheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively. R^2 and adjusted R^2 statistics are taken from separate OLS regressions of $\bar{r}_s^{DAX,Q}$ on *bullbear* and *quant*.

until survey wave February 2020. To account for heteroskedasticity and autocorrelation in the error term, I use the Newey and West (1987) estimator to estimate standard errors. Because the forecast horizon is six months, I follow Greenwood and Shleifer (2014) and set the maximum lag in the Newey-West estimation to six. The results in columns 2 and 3 (specifications (1) and (2)) suggest that *bullbear* is not predictive for realized returns. For both models, the null hypothesis that the coefficients on *bullbear* are 0 cannot be rejected at a reasonable significance level. The variable also does not explain much of the variation in returns, whereby R^2 seems to depend strongly on the sample period. More specifically, while *bullbear* explains only about 0.17% (-0.12% adjusted) of the variation in realized returns in the full sample, it explains about to 3.40% (2.92% adjusted) in the sample starting in 2003. In contrast, I find strong evidence that the variable *quant* has predictive power for realized returns. As documented in the last column of Table 4.14 (specification (3)), the coefficient on *quant* is positive, larger than 1 and has a p-value of 2.9% (not reported). Moreover, the variation in *quant* accounts for about 6.76% of the variation in realized returns, which is nearly two times the share explained by *bullbear* in column 3 (specification (2)). The results remain qualitatively unchanged when I consider excess returns, i.e. when I subtract the risk-free rate at the time of the forecasts from realized returns and the quantitative DAX forecasts (not reported). This result contradicts the finding of Greenwood and Shleifer (2014) that survey measures of expected return are negatively correlated with actual returns.

Having shown that *quant* is predictive for realized returns, I next compare the forecast accuracy of the variable to that of the historical average realized return. I use end-of-month values of the DAX index to calculate the historical average six-month DAX return prevailing in survey wave s, which began in month m as

$$\bar{r}_s^{DAX} = (m-1)^{-1} \sum_{i=1}^{m-1} r_{i-6;i}^{DAX}, \tag{4.13}$$

where i indexes months since the start of the calculation of the DAX index, which is December 1964 in my data source Eikon Datastream. Since I use all available six-months returns since December 1964, $\bar{r}_s^{DAX}$ changes only moderately between survey waves. Between December 1991 and February 2020, the historical average ranges from 4.58% to 6.04%, with a mean of 5.36% and a standard deviation of 0.27%. To compare accuracies of the two forecasts, I follow the approach outlined in Diebold and Mariano (1995), Harvey et al. (1997) and Rapach and Zhou (2013) and test whether the forecast errors made by the respondents of the ZEW FMS are smaller than those for DAX forecasts made with the historical average. My null hypothesis thus is

$$H_0 : MSFE^{histavg} \leq MSFE^{quant},$$

where $MSFE^{FE}$ is the mean squared forecast error of forecast $FE \in \{quant, histavg\}$. To carry out this test, I calculate the modified Diebold–Mariano test statistic (Equation (8) in Harvey et al., 1997, p. 283). In my case, the parameters n (the number of periods) and h (the forecast horizon), are 205 and 6, respectively. The data implies a test statistic of 0.4644. According to Harvey et al. (1997), the modified Diebold–Mariano test statistic follows a Student-t distribution. Using the cumulative distribution function of the Student-t distribution, I arrive at a p-value of 32.14%. The null hypothesis thus cannot be rejected, suggesting that the forecast accuracy of *quant* is not higher than that of the historical average.

4.7.2 Cross-sectional Differences In Forecast Accuracy

Having shown that the aggregate quantitative DAX forecast has predictive power for realized six-months DAX returns, I next explore whether there are differences in forecast accuracy between subgroups of the ZEW FMS panel formed by the personal characteristics available to me. To ensure that a forecaster always belongs to exactly one group in the comparisons, I only distinguish by time-invariant characteristics. I distinguish by age cohort, professional experience in conducting DAX forecasts, the self-assessed level of expertise in conducting DAX forecasts, whether the respondents take interest in the ZEW FMS results on stock markets in general and the respondents' main occupation. This allows me to relate potential differences in forecast accuracy to the respective differences in the documented relationships between economic conditions and DAX return expectations documented in Chapter 4.6.3. For the comparisons of forecast accuracy, I use the same approach as in Chapter 4.7.1, i.e. I calculate the subgroup-specific averages of realized returns and *expret* as in Equations (4.10) and (4.12) and use the adjusted Diebold–Mariano test statistic to evaluate whether one forecast is better than another. Given that the availability of the personal characteristics is concentrated at the end of the sample period (see Chapter 4.3.1), I might face a problem with small group sizes, implying that the average DAX return forecasts of some groups are very volatile. To alleviate

Table 4.15: Differences in forecast accuracy: professional experience in conducting DAX forecasts

B → A ↓	DAX forecasts: regular	DAX forecasts: sometimes	DAX forecasts: never
DAX forecasts: regular	-	-1.4864 (92.99%)	0.2544 (39.99%)
DAX forecasts: sometimes		-	0.6928 (24.50%)
DAX forecasts: never			-

Note: This table reports the results of pairwise comparisons of the mean squared forecast errors (MSFE) made by three subsets of the ZEW FMS panel: respondents who regulary conduct DAX forecasts outside of the ZEW FMS, respondents who sometimes conduct DAX forecasts outside of the ZEW FMS and respondents for never conduct DAX forecasts outside of the ZEW FMS. The table reports the adj. Diebold–Mariano statistic and the corresponding p-value for each comparison. The null hypotheses of the tests are given by $H_0 : MSFE^B \leq MSFE^A$, where the row determines A and the column determines B. Given that the tests are symmetric, I report only one result for each pair. For a pair (A,B), the adj. Diebold–Mariano statistic and p-value of a test of whether A is a more precise forecast than B, are the inverse of the the adj. Diebold–Mariano statistic and 1 minus the p-value, respectively, of the test of whether B is a more precise forecast than A.

this problem, I restrict the sample used to evaluate differences in forecast accuracy to the years 2012–2020. In this subsample, the personal characteristics of interest are available for at least 50% of the panel members and the minimum size per group and survey wave is not smaller than 15 for the large majority of groups.

Tables 4.15 to 4.18 report the adjusted Diebold–Mariano statistics and the corresponding p-values for the pairwise comparisons of mean squared forecast errors. The null hypotheses of the respective tests are $H_0 : MSFE^B \leq MSFE^A$, where the rows determine A and the columns determine B. Since the Diebold–Mariano test statistic of a test with $H_0 : MSFE^B \leq MSFE^A$ has the opposite sign as the test statistic of that with $H_0 : MSFE^A \leq MSFE^B$, I choose to report only the result of one of the two comparisons between A and B.[16]

Table 4.15 reports the results from the pairwise comparisons of the three categories of professional DAX forecasting experience. For all pairwise comparisons, judged by a 95% threshold for statistical significance, the evidence suggests that these forecasts are equivalent in terms of forecast accuracy. The difference in mean squared forecast errors is the largest between regular and irregular DAX forecasters. The respective test statistic implies a p-value of about 7%.

The results of the pairwise comparisons of the three groups of self-assessed expertise in conducting quantitative DAX forecasts reported in Table 4.16 suggest that forecast accuracy increases with expertise, albeit only when a 10% threshold for statistical significance is used. In terms of forecast accuracy, a high level of expertise dominates both medium and low levels of expertise and a medium level of expertise dominates a low level of expertise. The differences in forecast accuracy cannot be attributed to differences in how the groups form

[16] The p-value of a test of whether A is a more precise forecast than B is 1 minus the p-value of the test of whether B is a more precise forecast than A.

Table 4.16: Differences in forecast accuracy: expertise in conducting quantitative DAX forecasts

B → A ↓	Low expertise	Medium expertise	High expertise
Low expertise	-	-1.4696 (92.76%)	-1.4939 (93.08%)
Medium expertise		-	-1.3788 (91.44%)
High expertise			-

Note: This table reports the results of pairwise comparisons of the mean squared forecast errors (MSFE) made by three subsets of the ZEW FMS panel: respondents who assess their own expertise in conducting quantitative DAX forecasts as low, respondents who assess their own expertise in conducting quantitative DAX forecasts as medium and respondents who assess their own expertise in conducting quantitative DAX forecasts as high. The table reports the adj. Diebold–Mariano statistic and the corresponding p-value for each comparison. The null hypotheses of the tests are given by $H_0 : MSFE^B \leq MSFE^A$, where the row determines A and the column determines B. Given that the tests are symmetric, I report only one result for each pair. For a pair (A,B), the adj. Diebold–Mariano statistic and p-value of a test of whether A is a more precise forecast than B, are the inverse of the the adj. Diebold–Mariano statistic and 1 minus the p-value, respectively, of the test of whether B is a more precise forecast than A.

their DAX expectations conditional on economic conditions (see column 3 of Table 4.11).

When I compare the forecasts of those respondents who report to taking interest in the results of the ZEW FMS on stock markets in general to those who are not, I find the forecast accuracy to be equivalent. The adjusted Diebold–Mariano statistic and the implied p-value for the respective test are -0.5684 and 71.45%, respectively. When I re-estimate specification (4) of Table 4.11 for the subsample covering the years 2012–2020, I also do not find any differences in DAX expectations conditional on economic conditions.

The results documented in Table 4.17 suggest that the respondents' age cohorts do not matter for forecast accuracy.[17] Of the six possible pairwise comparisons, none of the respective null hypotheses can be rejected at the 5% level. Only the null hypothesis of the test of whether the forecasts of age cohort 4 are more precise than those of age cohort 2 can be rejected at the 10% significance level. Consistent with the notion that forecast accuracy and the relationships between DAX expectations and economic conditions are related, the absence of heterogeneity of forecast accuracy across age cohorts coincides with the absence of heterogeneity of DAX expectations conditional on economic conditions, the latter being valid both in the full sample (see column 5 of Table 4.10) and the subsample from 2012–2020.

Lastly, Table 4.18 reports the results of pairwise comparisons of the forecast accuracy of the different main occupations represented in the ZEW FMS panel. Given that there are 10 different groups, the issue with too small group sizes is the most pronounced for this personal characteristic, which should be kept in mind when interpreting the results. There are three comparisons for which the null hypotheses can be rejected at the 5% threshold. These are "Trading" vs. "Management", "Financing" vs. "Management", and "Security Research" vs.

[17]See Chapter 4.6.3 for the definition of age cohorts.

Table 4.17: Differences in forecast accuracy: age cohorts

B → A ↓	Cohort 1	Cohort 2	Cohort 3	Cohort 4
Cohort 1	-	-1.0402 (84.96%)	-0.5727 (71.59%)	0.3846 (35.07%)
Cohort 2		-	0.9567 (17.06%)	1.3367 (9.22%)
Cohort 3			-	1.0612 (14.56%)
Cohort 4				-

Note: This table reports the results of pairwise comparisons of the mean squared forecast errors (MSFE) made by three subsets of the ZEW FMS panel: respondents who assess their own expertise in conducting quantitative DAX forecasts as low, respondents who assess their own expertise in conducting quantitative DAX forecasts as medium and respondents who assess their own expertise in conducting quantitative DAX forecasts as high. The table reports the adj. Diebold–Mariano statistic and the corresponding p-value for each comparison. The null hypotheses of the tests are given by $H_0 : MSFE^B \leq MSFE^A$, where the row determines A and the column determines B. Given that the tests are symmetric, I report only one result for each pair. For a pair (A,B), the adj. Diebold–Mariano statistic and p-value of a test of whether A is a more precise forecast than B, are the inverse of the the adj. Diebold–Mariano statistic and 1 minus the p-value, respectively, of the test of whether B is a more precise forecast than A.

"Wealth Management". While Table 4.13 suggests that there are differences with respect to which variables these occupations consider when forecasting DAX returns, these differences are small and unsystematic (e.g. "Trading" and "Financing" seem to consider *ep* while "Management" seems not, whereas "Financing" and "Management" seem to consider *comp* while "Trading" seems not). The results reported in Table 4.13 thus do not suggest that the detected differences in forecast accuracy across main occupations can be traced back to differences in how they forecast DAX returns conditional on measures of economic conditions.

4.8 Summary And Discussion

Motivated by the contradictory empirical evidence on the time-variation in expected stock returns, I have studied the stock market expectations of German financial market experts. My aim was to get a better understanding of the sources of the variation in expected returns, to provide new evidence on the relationship between expected returns and economic conditions and to evaluate the financial experts' forecasting performance. My main findings are that i) respondents strongly disagree about how important macroeconomic and financial variables are related to DAX returns, ii) the measured relationships between my quantitative survey measure of DAX return expectations and measures of economic conditions are largely consistent with the view that expected returns are counter-cyclical, iii) in some cases, the scale of the expectation variable, i.e. metric resulting from a quantitative forecast or ordinal resulting from a qualitative forecast, matters for the measured direction of the relationship between DAX expectations and economic conditions and iv) an aggregated version of my quantitative survey measure of DAX return expectations positively predicts an

Table 4.18: Differences in forecast accuracy: main occupation

B → A ↓	Economic research	Trading	Financing	Management	Security research	Fund/portfolio management	Investment advice	Wealth manage-ment	Risk manage-ment	Other
Economic research	-	0.2243	0.6003	1.2187	0.4773	0.4779	0.8814	1.5694	0.7747	1.0172
		(41.15%)	(27.49%)	(11.30%)	(31.71%)	(31.69%)	(19.01%)	(5.99%)	(22.02%)	(15.58%)
Trading		-	1.1061	1.8370	0.0482	0.2174	0.3349	0.7200	1.0715	1.1418
			(13.57%)	(3.46%)	(48.08%)	(41.42%)	(36.92%)	(23.66%)	(14.33%)	(12.82%)
Financing			-	1.8257	-0.3785	-0.5906	-0.2143	0.1300	0.9456	0.7286
				(3.55%)	(64.71%)	(72.19%)	(58.46%)	(44.84%)	(17.34%)	(23.40%)
Management				-	-1.0269	-1.5793	-0.9112	-0.5968	-0.9162	-0.3923
					(84.65%)	(94.12%)	(81.78%)	(72.40%)	(81.91%)	(65.21%)
Security research					-	0.0779	0.6539	1.6743	0.5989	0.8086
						(46.90%)	(25.73%)	(4.86%)	(27.53%)	(21.04%)
Fund/portfolio management						-	0.2676	0.9053	0.8449	1.1609
							(39.48%)	(18.38%)	(20.01%)	(12.43%)
Investment advice							-	0.9214	0.4961	0.6367
								(17.96%)	(31.05%)	(26.29%)
Wealth management								-	0.2346	0.3831
									(40.75%)	(35.12%)
Risk management									-	0.1360
										(44.61%)
Other										-

Note: This table reports the results of pairwise comparisons of the mean squared forecast errors (MSFE) made the different main occupations in the ZEW FMS panel. The table reports the adj. Diebold–Mariano statistic and the corresponding p-value for each comparison. The null hypotheses of the tests are given by $H_0 : MSFE^B \leq MSFE^A$, where the row determines A and the column determines B. Given that the tests are symmetric, I report only one result for each pair. For a pair (A,B), the adj. Diebold–Mariano statistic and p-value of a test of whether A is a more precise forecast than B, are the inverse of the the adj. Diebold–Mariano statistic and 1 minus the p-value, respectively, of the test of whether B is a more precise forecast than A.

aggregated measure of realized returns, but is not superior to a simple average of historical DAX returns.

These results contradict the empirical findings from the literature studying expected returns via survey data, which raises the question of why this is the case. From my results, I am not able to give a definite answer to this question. Two explanations are, however, plausible. First, as my results indicate, a potential explanation for why previous studies have documented pro-cyclical expected returns might be measurement error, for example, because the researchers study a qualitative measure of stock return expectations. The list of surveys used in the literature on stock return expectations compiled in Table 4.1, however, reveals that most studies are based on quantitative measures of stock return expectations. Measurement error might thus only play a minor role here.

The second possible explanation might be that the differences in the results are due to the differing backgrounds of the respondents. Table 4.1 shows that most studies are based on data from surveys among households or individual investors, whereas my results are based on data from a survey among financial market experts. It is reasonable to assume that financial market experts form stock return expectations that are more in line with the empirical evidence from studies based on realized stock returns, either because they know the literature or, because they have learned the relationship between stock returns and economic conditions while working in the financial sector. The findings of Söderlind (2010), who studies the expectations of economists, point into this direction. Although he also finds that it is negatively correlated with the dividend–price ratio, Söderlind (2010) documents that his survey measure of stock return expectations is higher in recession periods, which is in line with what I find. Interesting questions for future research are thus how the format of the survey question used to measure expected returns affects the measured relationship between expected returns and proxies for expected returns and whether individuals with a background in economics or finance hold systematically different stock return expectations than households or individual investors.

Chapter 5

Conclusions

This thesis has studied research questions concerning the propagation and amplification of shocks, and the expectation formation of financial market participants. The aim of this thesis was to contribute to our understanding of how risk builds up within the financial system and how financial market participants form the expectations that underlie their investment decisions. Both issues are of great significance for our understanding of the drivers of financial cycles and how these impact the real economy.

Chapter 2 dealt with the questions of how the introduction of the Basel III bank regulation Liquidity Coverage Ratio affects the stability of the financial system and whether an increase in the financial system's stability comes at the cost of a lower supply of bank loans to the real sector. It was found that the regulation's aggregate effect is to lower the aggregate supply of bank loans to the real sector and to destabilize the creditors of banks. The most important insight was that the regulation shifts risk from banks to their creditors. Since banks fund a larger share of their balance sheet with long-term bonds under the regulation, their creditors become more exposed to fire sale and interest rate risk, and ultimately to shocks originating from the real sector.

Chapter 3 asked whether systematic over-optimism on the part of bank managers affects the amount of credit that they supply to the real sector. The chapter presented evidence that suggests that bank managers' decisions on the volume of new loans partially depend on past realizations of economic fundamentals, implying that loan growth and economic fundamentals are systematically disconnected. Moreover, it was shown that over-optimism on the part of bank managers spills over to their equity investors, who seem to interpret high bank manager sentiment as a positive signal for the risk associated with bank loan growth.

Lastly, Chapter 4 studied the stock market expectations of financial market experts. The three main findings were that the financial market experts differ considerably in how they incorporate macroeconomic and financial information into their DAX forecasts, that the chapter's main survey measure of expected DAX returns is on average higher when economic conditions are bad and that an aggregated measure of the financial market experts' stock return forecasts has weak predictive power for actual returns, but is a less precise forecast than a simple average of historical stock returns.

To conclude, this thesis has shown that the use of agent-based modeling techniques, and the analysis of text and survey data are fruitful approaches that help us to improve our understanding of the drivers financial cycles and their real implications. The results of the analyses of the text and survey data indicate that it is necessary to relax the rational expectations assumption in order to gain a better understanding of the underlying drivers of financial and credit cycles.

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Short CV

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EMPLOYMENT

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EDUCATION

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RESEARCH INTERESTS

- Banking: Bank business models, bank regulation, bank risk
- Expectation formation: survey-based measures of stock market and macroeconomic expectations
- Agent-based financial economics: modeling of financial markets and systems, model calibration and validation.

WORKING PAPERS

1. Riedler, J., and Brückbauer, F. (2017). Evaluating Regulation within an Artificial Financial System: A Framework and its Application to the Liquidity Coverage Ratio, ZEW - Centre for European Economic Research Discussion Paper No. 17-022, Mannheim.
2. Brückbauer, F. (2020). Do Financial Market Experts Know Their Theory? New Evidence From Survey Data, ZEW - Centre for European Economic Research Discussion Paper No. 20-092, Mannheim.
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