UNIVERSITY OF MANNHEIM

Essays on Financial Reporting Incentives and Bank Transparency

Inauguraldissertation zur Erlangung des akademischen Grades eines Doktors der Wirtschaftswissenschaften der Universität Mannheim

vorgelegt von

Nicolas Rudolf
Stuttgart

Dekan: Prof. Dr. Christian Becker
Referent: Prof. Dr. Jannis Bischof
Korreferent: Prof. Dr. Holger Daske

Tag der mündlichen Prüfung: 2. Juli 2020

Table of Contents

List of Figures

List of Tables

Nomenclature

AQR	Asset Quality Review
CEO	Chief Executive Officer
CFO	Chief Financial Officer
CIO	Chief Information Officer
CRO	Chief Risk Officer
CPA	Certified Public Accountant
ECB	European Central Bank
GDP	Gross Domestic Product
IMF	International Monetary Fund
LLP	Loan Loss Provision
NBER	National Bureau of Economic Research
NPL	Non-Performing Loan
OLS	Ordinary Least Squares
PCA	Principle Component Analysis
SSM	Single Supervisor Mechanism

Introduction

The global financial crisis placed bank transparency in the limelight of public interest (Financial Times, 2010). A major source of bank transparency is banks' financial reporting that helps to inform depositors, regulators, supervisors, and capital market participants about banks' financial position, performance, business activities, and in particular risk-taking (Bushman and Williams, 2015; Freixas and Laux, 2012).[1] However, accounting information from financial statements is only a noisy representation of the underlying economic reality as the rules that govern the reported numbers often require the exercise of judgement (Bushman, 2016).

The discretion inherent to accounting standards has two faces (Kanagaretnam, Lobo and Yang, 2004). On the one hand, accounting discretion can increase transparency by allowing managers to convey private information to outsiders when having superior knowledge about a transaction that can otherwise not be reflected in the accounting system (e.g., Beaver, Eger, Ryan and Wolfson, 1989; Wahlen, 1994). On the other hand, managerial discretion can also lead to the opportunistic application of accounting rules driven by reporting incentives that, in turn, undermine bank transparency (e.g., Vyas, 2011; Bischof, Laux, and Leuz, 2020).

One major accounting choice in the banking industry that involves substantial managerial discretion is the accounting for loan losses (Liu and Ryan, 2006; Barth and Landsman, 2010; Beatty and Liao, 2014; Gebhard and Novotny-Farkas, 2011). Loans are economically important for banks as they are the largest asset on most banks' balance sheets and loan loss provisions represent the largest bank accrual for the majority of banks (Beatty and Liao, 2014; Acharya and Ryan, 2015).

[1] Bank transparency has many facets and ultimately arises from information collection, verification, and dissemination to stakeholders outside the bank who utilize this information in their decision making (Bushman, 2014; Freixas and Laux, 2012).

During and after the global financial crisis (2007-2008) the accounting rules for loan loss provisions were frequently blamed for encouraging banks to recognize delayed and insufficient provisions as cushions against future loan losses (Dugan, 2009; Curry, 2013).[2] This critique ultimately resulted in the introduction of redesigned and more forward-looking provisioning standards in Europe (IFRS 9) and the United States (ASU 2016-13).

However, banks' reporting choices can be influenced by a variety of incentives and pressures that go far beyond the design of accounting standards per se (Beatty and Liao, 2014; Bushman, 2014). Bank-specific incentives such as capital market pressure, private ownership, taxation, or regulation are associated with discretion in recognizing loan losses (e.g., Beatty et al., 1995, 2002; Collins et al., 1995; Ahmed et al., 1999; Bushman and Williams, 2012). Furthermore, individual manager incentives and preferences that are correlated with risk-taking, capital structure, and corporate reporting choices in general could play a significant role for banks' provisioning behavior (Armstrong et al., 2010; Bamber et al., 2010; Bertrand and Schoar, 2003; Ge et al., 2011).

Besides the discretion that arises from accounting standards or individual manager preferences, the institutional design and in particular enforcement can influence firms' reporting behavior (Christensen, Hail, and Leuz, 2013; Holthausen, 2009). In the banking sector, dedicated bank supervisors tend to dominate the public enforcement of reporting regulation (Bischof, Daske, Elfers, and Hail, 2020). However, the supervisory and regulatory toolkit is not limited to direct enforcement by intervention into banks' business activities through penalties and other corrective actions. Bank supervisors can also take alternative actions to influence bank behavior such as

2 The adverse consequences of delaying loan loss provisioning are manifold, feedback to the real economy and impair financial stability (Bushman and Williams, 2016; Ahmed, Takeda, and Thomas, 1999; Beatty and Liao, 2011).

disclosures about banks' risk exposure (e.g., through stress tests) in order to promote market discipline that eventually inhibits excessive risk-taking and fosters transparency (Goldstein and Sapra, 2014; Goldstein and Yang, 2019; Bischof and Daske, 2013).

This thesis consists out of three chapters that all add to the literature on bank transparency. While the first chapter explores determinants of bank transparency at the most granular level by looking at individual managers and how they shape financial reporting decisions, the second and the third chapter document the role of bank, country, and supranational reporting incentives for banks' reporting choices. Within the next paragraphs, I describe the chapters of my thesis in more detail.

In Chapter 1, I start with an investigation of individual managers and their inherent characteristics as potential determinants of banks' financial reporting decisions. The first chapter is based on a working paper that I wrote together with Jannis Bischof (University of Mannheim) entitled "Manager Characteristics and Banks' Loan Loss Provisioning". While prior literature provides ample evidence on a variety of incentives and pressures that explain the variation in provisioning behavior across banks and over time, we know much less about variation in provisioning behavior within banks (Beatty and Liao, 2014; Bushman, 2014). Because the incentives and preferences of individual managers are associated with corporate reporting choices in general (Armstrong et al., 2010; Bamber et al., 2010; Ge et al., 2011), it is highly plausible that the characteristics of individual managers also play a role in a bank's loan loss provisioning. A better understanding of this role is particularly important because recent regulation in the banking sector is targeting the qualifications of individual managers (e.g., ECB, 2018a). These regulations can only be effective if individual managers' actions are meaningfully correlated with reporting choices that affect bank transparency such as the loan loss provisioning behavior.

We build on research in finance (Malmendier et al., 2011; Nguyen et al., 2017) and accounting (Ahmed et al., 2019; Livne et al., 2011; Bushman et al., 2018) that documents the influence of manager characteristics on corporate policies and examine whether idiosyncratic management styles help explain banks' loan loss provisioning choices. In contrast to prior literature that primarily focuses on specific traits and incentives, we identify the impact of unobservable traits that in combination translate into individual management styles. We first disentangle and quantify this individual manager influence from firm-specific factors. Furthermore, we explore how individual management styles interact with top management team composition.

To analyze the role of manager styles, we build on a dataset of top managers of US banks over the period from 1993 to 2015. We combine information from different datasets that include observable characteristics (e.g., compensation, education, experience), firm characteristics (e.g., size, risk, performance), and accounting choices. In a first step of our analysis, we test for the association between discretionary loan loss provisions and manager characteristics. In our analysis, we distinguish between observable and unobservable characteristics. We capture unobservable characteristics through a three-way fixed-effects structure that exploits the interconnectedness between managers that switch to another sample bank and managers that remain at the same bank (Abowd et al., 1999; hereafter AKM method). These fixed effects capture all time-invariant manager characteristics and can be described as management styles for observable management choices even if the underlying factors explaining these choices remain unobservable. Our results suggest that observable manager characteristics explain only a small amount of the variation in banks' discretionary loan loss provisions, whereas idiosyncratic, yet unobservable attributes of individual managers account for approximately 19% of this variation (compared to 12% for unobservable firm attributes). This finding does not imply that individual bank managers have little influence on accounting choices, but rather that managers exert this influence through their preferences, skills, or talent that are notoriously hard to measure but key to a full understanding of managers' role in the accounting process.

In the second step, we explore whether managers loan loss provisioning styles relate to other relevant corporate actions. We document a systematic correlation between the loan loss provisioning style and management styles for various corporate policies. For example, managers with a greater level of discretion in the loan loss provisioning choice also reveal a preference for a higher level of risk-taking and, on average, a lower quality of the loan portfolio. That is, managers loan loss provisioning styles are systematically related to other corporate actions.

In the third and final step, we build on the classification by Pitcher and Smith (2001) and distinguish between four different types of managers: technocrats, artists, craftsmen, and traditionalists. Our classification rests on the manager styles that we identified through the AKM method in the previous step. We use the different manager styles of members of a bank's top management to get a measure for the diversity of top management teams that is derived from observable preferences for specific corporate actions. Based on these measures, we analyze whether the composition of top management teams potentially mutes the role that idiosyncratic manager styles play in the loan loss provisioning choice. We show that diversity of manager styles in the top management team mutes the significant association between the individual manager style and the level of reporting discretion.

In Chapter 2, which is based on a working paper that I wrote together with Jannis Bischof (University of Mannheim) and Ferdinand Elfers (Erasmus School of Economics) entitled "Do

Supervisory Disclosures Lead to Greater Bank Transparency? The Role of Enforcement and Market Discipline", we empirically investigate how bank supervisors can influence the transparency of supervised firms through enforcement and supervisory disclosures.

In this project, we explore how a plausibly exogenous change in enforcement in conjunction with the supervisory disclosure of banks' asset quality affects bank transparency. We exploit the shift from a purely national banking supervision to a unified European supervisor to identify differences in supervisory reporting preferences. Since it is not straightforward to determine an objective and comparable measure of supervisory reporting preferences, we exploit the simultaneous Asset Quality Review (AQR) disclosures by the ECB. This assessment included a point-in-time assessment of the accuracy of the carrying values of banks' assets with a particular focus on the classification of non-performing exposures and loan loss provisions. However, most of the AQR adjustments were not reflecting violations of accounting rules, but rather signaled a shift in supervisory reporting preferences within a common accounting framework, with the ECB generally preferring higher levels of provisioning than the national supervisors previously in charge of bank supervision. We exploit this firm-level variation as well as the staggered shift to ECB supervision to analyze the change in affected banks' reporting behavior and transparency in a difference-in-difference framework.

We find that the ECB's disclosed reporting preference is reflected in banks reporting behavior and market liquidity in the following periods. We interpret this as evidence that banks' reporting choices are influenced by supervisory preferences beyond simple compliance with given accounting standards. The effect on banks reporting behavior is particularly pronounced for banks that experienced the greatest shift in supervisory characteristics. That is, banks whose prior national supervisory environment was characterized by low supervisory quality or had a higher likelihood of political capture before the SSM. We observe a corresponding effect on market liquidity that is more pronounced for banks that are likely to be subject to market discipline. Furthermore, we identify the timeliness of loan loss provisions as potential channel through which the shift in reporting translates into reduced information asymmetry. Overall, our findings suggest that supervisory disclosures are potentially effective in establishing greater transparency of the banking sector, but depend on the presence of firm-level incentives that help to establish market discipline.

In Chapter 3, which is based on a working paper with the title “Legal Efficiency and Non-Performing Loans along the Economic Cycle”, I study how cross-country differences in legal efficiency interact with non-performing loans along the business cycle. Many banks faced elevated levels of NPLs after the global financial crisis and the sovereign debt crisis. However, NPLs still represent a burden for banks balance sheets with European banks holding more than 580 billion euros of non-performing exposures at the end of March 2019 (ECB, 2019). I start this study from the observation that in the aftermath of the severe economic downturn in the Eurozone caused by the global financial crisis and the sovereign debt crisis, only a subset of countries was able to substantially decrease their NPLs although most countries were facing favorable economic conditions .

One explanation for this phenomenon could be the severe differences in contract enforcement and insolvency regimes across Europe that exacerbate uncertainty for banks and lead to slow loan write-offs. Banks often have to wait for courts deciding on cases in order to determine the amount that has to be written off. A typical foreclosure process (for a mortgage loan) in northern Europe can take up to three years, while it can be up to eight years in Greece (Fitch, 2016). However, despite the high importance of a swift process to resolve non-performing loans, there is a lack of research on the impact of bank-specific or institutional determinants such as legal efficiency that potentially influence the duration of the NPL cycle.

In the first step, I employ a proportional hazard model on the country-level to answer the question whether legal efficiency and economic growth influence the duration of NPL cycles. I document that the increasing NPL phase is mainly associated with macroeconomic factors such as economic growth. However, the duration until a bank can decrease its NPL levels after the country enters an economic growth phase is substantially shorter for banks in countries with higher legal efficiency. In the second step, I employ bank-level data to compare how macroeconomic, bank-specific factors and institutional differences in legal efficiency are associated with NPLs over the economic cycle. I employ various proxies for legal efficiency from prior literature (Djankov La Porta, Lopez-de-Silanes and Shleifer, 2003; Djankov, Hart, McLiesh, and Shleifer, 2008). My results consistently document that the duration and costs of contract enforcement and insolvency procedures are negatively associated with NPL ratios during economic growth phases. Taken together my analyses documents that legal efficiency is significantly associated with NPL resolution whereas the increasing NPL phase is mainly determined by economic growth.

This thesis provides answers to three important research questions related to financial reporting incentives and bank transparency. In Chapter 1, I document that a large proportion of the variation in banks loan loss provisioning behavior is explained by individual bank manager characteristics. Furthermore, the research presented in Chapter 2 documents that supervisory disclosures can foster market discipline that lead to higher overall bank transparency. Finally, in Chapter 3, I provide evidence on the association between legal efficiency and non-performing loans along the business cycle that can help to inform the regulatory and supervisory debate on measures to deal with elevated NPL levels that are likely to emerge after the recent virus-related economic downturn in many countries.

Chapter 1

Manager Characteristics and Banks' Loan Loss Provisioning

1.1. Introduction

What determines banks' loan loss provisioning choices? Prior literature provides ample evidence on a variety of incentives and pressures that explain the variation in provisioning behavior across banks and over time (Beatty and Liao, 2014; Bushman, 2014). However, we know much less about variation in provisioning behavior within banks (Bushman and Williams, 2015). Individual managers shape corporate actions such as risk-taking and capital structure choices (Bertrand and Schoar, 2003; Graham, Harvey & Puri, 2013). Their incentives and preferences are associated with corporate reporting choices in general (Armstrong et al., 2010; Bamber et al., 2010; Ge et al., 2011). However, little evidence exists on management's role in the timing of loan loss recognition (Beatty and Liao, 2014). A better understanding of this role is especially important because recent regulation in the banking sector is targeting the qualifications of individual managers (e.g., ECB, 2018a). The potential impact of these regulations hinges on the influence that individual managers actually have on critical actions such as the loan loss provisioning choice.

Against this background, we build on research in finance (Malmendier et al., 2011; Nguyen et al., 2017) and accounting (Ahmed et al., 2019; Livne et al., 2011; Bushman et al., 2018) that investigates the influence of manager characteristics on corporate policies and examine whether idiosyncratic management styles help explain banks' loan loss provisioning choices. In contrast to prior literature that primarily focuses on specific traits and incentives, we identify the impact of unobservable attributes that, in combination, translate into an individual management style. We disentangle the overall influence of these idiosyncratic styles on the reporting outcome from firm-specific factors. In addition, we analyze how these management styles interact with top management team composition.

To address these questions, we construct a comprehensive dataset of top executives of US banks over the period from 1993 to 2015. The dataset combines information about manager characteristics (e.g., compensation, education, experience), firm characteristics (e.g., size, risk, performance), and accounting choices. In a first step of our analysis, we test for the association between discretionary loan loss provisions and manager characteristics. We distinguish between observable and unobservable characteristics. We capture unobservable characteristics through a fixed-effects structure that exploits the interconnectedness between managers that switch to another sample bank and managers that remain at the same bank (Abowd et al., 1999; hereafter AKM method). These fixed effects are supposed to capture latent time-invariant manager styles that describe preferences for observable management choices even if the underlying factors explaining these choices remain unobservable.

In a second step, we analyze how the role of idiosyncratic manager styles in the choice of loan-loss provisions relates to other relevant corporate actions. To this end, we compare the time-invariant manager style that manifests in the choice of loan loss provisions with other management choices that affect a bank's risk-taking (such as leverage or loan quality). To better understand commonalities in the role that individual managers play in these different decisions, we test whether these fixed effects (i.e., the different manager styles) are associated with observable demographics, occupational status, or education of individual managers and with their risk-taking incentives. Put differently, we test whether the unobservable style that the fixed-effects capture under the AKM method is systematically correlated with observable factors. We follow Baik et al. (2011) and also employ principal components analysis to combine these different factors and construct a manager-specific score to overcome the noise inherent to the measurement of individual characteristics and incentives.

In a third and final step, we build on the classification by Pitcher and Smith (2001) and distinguish between four different types of managers: technocrats, artists, craftsmen, and traditionalists. Our classification rests on the manager styles that we identified through the AKM method. We use the different manager styles of members of a bank's top management to get a measure for the diversity of top management teams that is derived from observable preferences for specific corporate actions. Based on these measures, we analyze whether the composition of top management teams potentially mutes the role that idiosyncratic manager styles play in the loan loss provisioning choice.

Our results suggest that observable manager characteristics and incentives explain only a relatively small amount of the variation in banks' discretionary loan loss provisions. We rather find that idiosyncratic, yet unobservable attributes of individual managers account for approximately 19% of this variation (compared to 12% for unobservable firm attributes). The low correlations between observable characteristics and reporting outcomes thus do not imply that individual bank managers have little influence on accounting choices. Managers exert this influence in an idiosyncratic way through their preferences, skills, or talent that are notoriously hard to measure but key to a full understanding of managers' role in the accounting process.

We find that some observable characteristics are correlated with the unobservable factors that reflect preferences for observable outcomes at the firm level. However, these correlations are little systematic and they vary substantially across different corporate policies that managers potentially influence. Most of the cross-sectional variation in manager styles remains, therefore, unexplained. The manager styles are still economically meaningful because the direction of the underlying preferences for certain corporate policies appears systematic. For example, managers with a greater level of discretion in the loan loss provisioning choice also reveal a preference for a higher level of risk-taking and, on average, a lower quality of the loan portfolio. That is, managers who have a distinct impact on the loan loss provisioning do exert their influence on other corporate actions in a systematically related way. We exploit these relations to construct four different categories of managers that we label according to Pitcher and Smith (2001). Managers whom we label as 'technocrats' and 'artists' employ systematically more discretion in the provisioning choice than 'craftsmen' and 'traditionalists'. These associations are statistically significant and economically meaningful.

However, we also find evidence consistent with these top managers interacting with other members of the executive board. Diversity of manager styles in the top management team mutes the significant association between the individual manager style and the level of reporting discretion. Overall, these findings suggest that the focus of bank supervisors on the skills and qualifications of individual managers can be justified by the systematic impact that these characteristics have on relevant corporate policies, at least in combination with other members of the top management team. Yet, the evidence also implies that the focus should build on top managers' revealed preferences as reflected in key policies rather than on readily observable attributes.

Our study contributes to two different streams of the accounting literature. First, we add to the understanding of the determinants of banks' loan loss provisions. Going back to at least Beaver et al. (1989), the literature on the discretion and timing in recognizing loan losses has examined various bank-specific incentives such as capital market pressure, private ownership, taxation, or regulation (e.g., Beatty et al., 1995, 2002; Collins et al., 1995; Ahmed et al., 1999; Bushman and Williams, 2012) as well as variation over time (e.g., Liu and Ryan, 2006; Beck and Narayanmoorth, 2013). However, we know relatively little about the impact of individual bank managers on the provisioning choice. One recent exception is Ahmed et al. (2019) who document the association between managers' previous crisis experience and the timeliness of loan loss provisions during the financial crisis. We extend this result beyond a single attribute and show the influence of both observable and unobservable manager characteristics in crisis and non-crisis periods. This finding helps understand the impact of recent regulation that targets the qualifications and behavior of individual bank managers.

Second, we add to the growing literature on the impact of manager characteristics on reporting outcomes in general. This literature documents that manager styles help explain voluntary disclosure (Bamber et al., 2010), accounting choices (Ge et al., 2011; Dejong and Ling, 2013), disclosure tone (Davis et al., 2015), or tax avoidance (Dyreng et al., 2010). The role of individual managers in the reporting process is associated with individual attributes such as military experience (Law and Mills, 2017), masculinity (Jia et al., 2014), narcissism (Ham et al., 2018; Young et al., 2016), religiosity (Dyreng et al., 2012), materialism (Bushman et al., 2018), gambling attitudes (Christensen et al., 2018), tenure (Ali and Zhang, 2015), gender (Francis et al., 2015), age (Huang, Rose-Green & Lee, 2012), ability (Demerjian et al., 2013), and overconfidence (Hribar and Yang, 2016; Schrand and Zechman, 2012). The identification of individual attributes in these prior studies typically relies on samples of managers who moved between firms and, therefore, tend to have unique characteristics. We borrow from the literature in finance and economics (e.g., Graham, Li and Qiu, 2012; Lopes de Melo, 2018) and use the AKM method to expand the sample. By exploiting the interconnectedness between moving and non-moving managers, we show that the inclusion of non-moving managers into the sample substantially increases the explanatory power of the manager characteristics. Related to this, we pick up recent insights on the importance of board composition (e.g., Li and Wahid, 2018; van Peteghem, Bruynseels & Gaeremynck, 2018) and present results consistent with the diversity of manager styles in a bank's top management muting the dominant influence of individual managers.

1.2. Prior research and empirical predictions

1.2.1. Empirical approaches to identify manager characteristics

Classic economic theory offers ambiguous predictions on whether the individual characteristics of managers have any influence on corporate decisions. Neoclassical theory views managers as homogeneous input into firms' production process and variation in executive characteristics do not play any role (Veblen, 1900; Bertrand and Schoar, 2003). Relatedly, the new institutional theory suggests that organizational boundaries, conventions, and norms constrain the impact of any individual on firm-level outcomes (e.g., DiMaggio and Powell, 1983).

In contrast to these predictions, Hambrick and Mason (1984)'s upper echelon theory builds on managers' personality, experience, and values being the main driver of organizational decisions within a firm. Put differently, the upper echelons theory suggests that two seemingly identical managers with a similar education, age, tenure, and compensation can vary in how they affect corporate actions because of their latent unobservable personality and ability. While the recent economic theory from Dessein and Santos (forthcoming) is consistent with these individual manager effects, it attributes the idiosyncratic manager styles to attention allocation rather than to cognitive biases of managers. Therefore, idiosyncratic manager effects could appear even when manager's information processing is optimal and not driven by behavioral biases.

Prior empirical literature offers evidence consistent with the upper echelons theory and the attention theory by Dessein and Santos (forthcoming). These studies differ in the empirical identification of the role of individual managers. A first set of studies focuses on a single managerial trait and investigates, for example, the association between firm policies and manager-specific variables such as gender (Francis et al., 2015), age (Huang et al., 2012), tenure (Ali and Zhang, 2015), masculinity (Jia et al., 2014), ability (Demerjian et al., 2013), cultural heritage (Brochet et al., 2019), and prior legal infractions (Davidson et al., 2015). While these studies provide relatively robust evidence on the existence of these associations, individual managerial traits likely manifest themselves not in isolation, but rather in certain combinations of specific attributes (e.g., Adams et al., 2018). The empirical design of these studies does, by construction, not disentangle the impact of the specific trait from other time-invariant firm attributes.

A second stream of literature exploits managerial mobility between firms to overcome the inherent identification challenges. The use of mover-dummy variables isolates the manager styles innate to managers that move between different firms. These manager styles capture bundles of latent individual traits rather than specific characteristics. Evidence suggests that they are, inter alia, associated with firms' forecasting behavior (Bamber et al., 2010), conference call tone (Davis et al., 2015), corporate tax avoidance (Dyreng et al., 2010), and earnings management (Ge et al., 2011). However, the sample selection in the first place is confined to managers who move between firms. If moving managers differ systematically from managers without any observable mobility, the sample restriction leads to biased estimates because of endogenous matching between managers and firms (Fee et al., 2013; Pan, 2017). For example, firms plausibly decide to replace managers concurrently with the decision about certain policy changes, and therefore, any changes in management style can overlap with the economic circumstances that caused the managerial turnover in the first place.

The third and most recent approach is the employment of the AKM sampling technique. The method accounts for the potential difference between moving and non-moving managers and, therefore, does not solely rely on moving managers. Instead, the AKM method exploits the connectedness between different groups of managers. Evidence that is derived from the application of the AKM method suggests that individual manager styles affect compensation (Graham et al., 2012), corporate social responsibility (Davidson et al., 2019), earnings management (Wells, 2020), audit fees (Lauck et al., 2020), and tax avoidance (Law and Mills, 2017). We extend this stream of literature and employ the AKM method to explore the role of individual bank managers in banks' loan loss provisioning choices. To alleviate remaining matching concerns, we additionally exploit a sub-sample of plausibly exogenous manager turnovers.

1.2.2. The role of individual managers in banks' loan loss provisioning choices

Banking is a highly regulated industry with regulation imposing relatively strong constraints on the individual manager (e.g., Beatty and Liao, 2014; Hollander and Verriest, 2016). For example, recent regulation (e.g., on management compensation) is increasingly limiting the influence of individual manager's incentives on bank-level decisions. At the same time, banking supervisors become more involved in the screening of individual manager characteristics during the recruiting process (e.g., Busch and Teubner, 2019). Against this background, the level of management discretion in banks is relatively more confined than in other industries. For these low-discretionary industries, the upper echelons theory and the attention theory predicts a lower influence of idiosyncratic manager preferences on corporate decisions (Hambrick, 2007; Crossland and Hambrick, 2007; Hambrick and Quigley, 2014; Dessein and Santos, forthcoming). Instead, firm-level discretion mainly arises from environmental conditions and governance structures in these types of industries.

On the other hand, in any regulated industry, it is unlikely that shareholders, boards, and supervisors will be able to write perfect contracts that entirely limit discretion. This is particularly critical for a task that is as inherently subjective and complex as the provisioning for future loan losses. Banks have to recognize loan loss provisions if it is probable that a loan is impaired and if the amount can be reasonably estimated. When bank managers assess these criteria, they frequently distinguish between general loan loss provisions for portfolios of homogenous loans (e.g., different classes of consumer loans) and specific provisions for large individual loans. They use complex statistical models for the estimation of general loan loss provisions with the input into these models being subject to substantial managerial judgment. The judgment is even greater when managers determine individual loan loss provisions for large commercial loans and, through these decisions, bank managers directly intervene into the corporate reporting choice. For these complex and subjective tasks, the upper echelons theory predicts an even increasing impact of individual characteristics and past experiences on corporate decision-making.

Overall then, the nature of regulation in the banking industry as well as the nature of the loan loss provisioning task result in opposite predictions leaving the role of individual managers in the shaping of banks' loan loss provisioning behavior as, ultimately, an empirical question.

1.2.3. The role of top management team composition

While recent empirical evidence tends to support the notion of individual managers being key to the explanation of corporate decisions, the literature also suggests that top management team diversity mitigates this impact (Adams and Ferreira, 2010; Garlappi, Giammarino and Lazrak, 2017). That is, group dynamics can influence organizational outcomes even without the presence of observable agency conflicts or information asymmetries. Prior evidence from non-banks exploits differences along observable characteristics such as age, tenure or education and is generally consistent with diversity also interacting with the managerial influence on corporate reporting choices (e.g., Li and Wahid, 2018, Van Peteghem et al., 2018).

It is less clear whether these dynamics also evolve in banks' loan loss provisioning decisions. The decisions about general and individual loan loss provisions depend on highly specific knowledge of individual managers. Educational and functional diversity is particularly pronounced for board members in the banking industry and potentially leads to substantial knowledge gaps (e.g., Berger et al., 2014; Macey and O'Hara, 2016). The difference in task knowledge eventually translates into the reliance on one individual manager. This is consistent with Graham et al. (2013)'s observations which suggest that oversight should "[...] use outsourced expertise in technical subjects such as valuing assets like mortgage-backed securities, residual assets or compliance with loan loss reserves" (p. 29).

There is very limited evidence on top management team diversity within banks. Extant literature documents that educational and functional heterogeneity can prove beneficial for bank innovations (Bantel and Jackson, 1989) and, especially, during mergers (Hagendorff, Collins & Keasy, 2010). We build on this literature and investigate whether the diversity of top management teams in banks moderates the influence of individual managers' discretion on loan loss provisions.

1.3. Data

We collect banks' financial accounting data from Compustat banks, stock market data from (CRSP) and manager data from ExecuComp[3] and BoardEx. Our sample period spans from 1993 to 2014 because of data requirements about future and prior non-performing loans. We identify 207 banks, 1,858 managers (9,893 observations) with available CRSP, Compustat, BoardEx, and ExecuComp data. We limit the dataset to 108 banks that employed at least one manager who switched to another bank during the sample period allowing us to separate firm and manager effect with the AKM sampling technique. That is, our final dataset with available information on manager characteristics from BoardEx and Execucomp includes 4,740 observations and 911 distinct managers that worked for 108 banks.[4] We focus on the five highest-paid managers within each bank, including positions such as CEO, CFO, CRO (Chief Risk Officer), CIO (Chief Information Officer), and General Counsel. While evidence from other industries suggests that CEOs and CFOs differ in their influence over reporting decisions (Jiang et al., 2010), it is ex ante unclear whether the idiosyncratic influence of bank managers on loan loss provisions is associated with a specific job title within the top management team.

[3] ExecuComp covers all banks that were included in the S&P 1500 at least for one year. ExecuComp is available for periods from 1992 onwards.

[4] That is, we capture roughly 50% of the full Execucomp-Boardex-Compustat sample, whereas the mover dummy variable method (e.g. Betrand and Schoar, 2003; Bamber et al., 2010) would restrict the sample to 98 managers that moved across banks (less than 11% of all managers in the full sample).

1.4. Measuring loan loss provisioning quality

For our investigation of manager's loan loss provisioning choice, we follow Beatty and Liao (2014) and measure banks loan loss provisioning quality by estimating a model that separates the loan loss provision in a systemic and a discretionary part using quarterly bank data from Compustat banks. If managers idiosyncratically influence the loan loss provision this should be reflected in the variation of the loan loss provision that is not explained by macroeconomic and firm fundamentals, such as changes in GDP or non-performing loans. Therefore, we use the residuals from the following pooled OLS regression that capture only variation unaccounted for by bank or macroeconomic fundamentals: [5]

$$(1)\ LLP_{j,t} = \alpha_0 + \beta_1 \Delta NPL_{j,t+1} + \beta_2 \Delta NPL_{j,t} + \beta_3 \Delta NPL_{j,t-1} + \beta_4 \Delta NPL_{j,t-2} + \beta_5 \Delta Loan_{j,t} + \beta_6 Regulatory\ Capital_{j,t-1} + \beta_7 Size_{j,t-1} + \beta_8 GDP_t + \beta_9 HPI_{j,t} + \mu_t + \varepsilon_{j,t}$$

Where $LLP_{j,t}$ denotes loan loss provisions scaled by lagged total loans, $\Delta NPL_{j,t}$ is the change in non-performing loans from period t to period $t-1$ scaled by total loans in $t-1$. We also include lagged ($\Delta NPL_{j,t-1}$) and forward looking ($\Delta NPL_{j,t+1}$) changes in non-performing loans because banks potentially use this information to approximate changes in loan portfolio risk in order determine the loan loss provision (Beatty and Liao, 2014). *Size* is the natural logarithm of total assets and captures bank resources, sophistication, and business model differences that could affect provisioning policies (Bhat et al., 2019. $\Delta Loan$ denotes changes in total loans and captures banks prior loan loss accruals (Nicoletti, 2018). We include the natural logarithm of Tier 1 regulatory capital ($Regulatory\ Capital$) to control for banks' incentive to manage regulatory

[5] Beatty and Liao (2014) find that this model most accurately predicts earnings restatements and comment letters. However, our results are robust to using the three other models from Beatty and Liao (2014), the model of Bushman and Williams (2012) or Liu and Ryan (2006).

capital through provisioning behavior (Liu and Ryan, 2006). We use gross domestic product (GDP) data from the Federal Reserve bank of St. Louis and house price index data (HPI) from the Federal Housing Finance Agency to capture changes in the macroeconomic environment. In addition, we include quarter fixed effects to account for macroeconomic changes affecting all banks in a given quarter. Standard errors are clustered by bank to control for time-series correlation within banks (Petersen, 2009).

We construct two proxies for discretionary loan loss provisions from equation (1). First, we calculate the natural logarithm of the absolute yearly mean residuals to capture the overall discretionary loan loss provisioning behavior. Second, we employ the yearly mean of the signed residuals as proxy for signed discretionary loan loss provisions. Positive residuals signal that managers provision more than predicted by the model, whereas negative residuals indicate underprovisioning. While both overprovisioning and underprovisioning could undermine bank transparency, positive residuals may signal proprietary management information about credit losses (Jiang et al., 2016). In contrast, negative residuals should rather point at discretionary understating of the loss provisions.

1.5. The role of individual managers in the LLP choice

1.5.1. Research design

Banks and their executives are highly interrelated through contracts and incentives. Therefore, a major methodological challenge is to separate the manager fixed effect from the impact of the firm on loan loss provisions. If a manager works at the same bank over the whole sample period, both effects would be perfectly collinear and therefore, indistinguishable. Prior studies solve this issue building on samples that require each manager to switch firms at least once during the sample period (mover method, e.g., Dyreng et al., 2010, Yang, 2012, Davis et al., 2015). This has primarily two disadvantages. First, the sample is limited to switching managers. Because managerial turnover is observed relatively infrequent this reduces the sample size significantly. Second, switching managers differ systematically in their characteristics from managers who stay at the same firm. This leads to sample selection bias, if differences in the likelihood of managerial mobility are correlated to managers' loan loss provisioning behavior.[6]

The AKM method circumvents both issues by solving the identification problem through the interconnectedness of managers and firms within groups. More specifically, while the mover method can identify a manager effect only if the person worked for at least two banks, the necessary and sufficient identifying condition within the AKM method is that a manager worked for a bank that employed at least one manager who switches the employer during the sample period (Abowd et al., 2002). Put differently, we can exploit information from all banks that employed at least one manager who switches the employer during the sample period. Additionally, all other managers who worked for these banks are included in our sample. Therefore, our sample includes also a large proportion of non-moving mangers, reducing potential selection bias while increasing sample size.

Studying the manager fixed effects has several advantages. First, it is not necessary to specify a relation between time-varying executive characteristics and firm characteristics. Second, by controlling for firm fixed effects, we can at least partially address reverse causality concerns due to firms selecting new executives for a specific provisioning style (Fee et al., 2013). Precisely,

6 In Table 2 we confirm that mover managers differ significantly across several observable characteristics from non-moving managers.

we can rule out selection bias resulting from matching based on time-invariant or the included time-varying manager and firm characteristics. We further address these concerns by using plausibly exogenous turnovers in a robustness test. Using the AKM method we estimate the following three-way fixed effects model to specify the manager and firm effect on discretionary loan loss provisions:

$$(2)\ DLLP_{i,j,t} = X_{i,t}\beta + W_{j,t}\,\gamma + \phi_j + \theta_i + \mu_t + \varepsilon_{i,j,t}$$

Where i denotes executives, j denotes firm and t denotes the year of the discretionary loss provision (DLLP). $X_{i,t}$ represents time-varying manager characteristics including compensation incentives (delta and vega), age and tenure of the manager. We measure risk-taking incentives (vega) with the dollar change in wealth linked to a 1% increase in stock return volatility.[7] The pay-performance sensitivity (delta) is measured with the dollar change in a manager's wealth to changes in a bank's stock price performance. Both measures are scaled with total cash compensation and log-transformed (Edmans et al., 2009).[8] $W_{j,t}$ represents time-varying firm characteristics and includes the market-to-book ratio and size to capture potential business model differences of banks that may vary over time. Furthermore, we include firm fixed effects (ϕ_j), manager fixed effects (θ_i) and year fixed effects (μ_t). The main variable of interest in our analysis is the manager fixed effect μ_t that captures all time-invariant manager characteristics such as managers gender, ability and personality.

[7] Risk-taking incentives from stock option compensation result from the asymmetric payoff function of stock options (Core and Guay, 2002). Option holders can benefit if the stock price rises above the strike price, however, vice versa option holders do not have to pay the difference in case the stock price declines. Nevertheless, option compensation can also affect individual risk-taking negatively due to the sensitivity of an executive's wealth to changes in stock price (delta). That is, a risk averse manager might be reluctant to take risks if his wealth is mainly invested in stock options and he has no ability to hedge this risk.

[8] We thank Lalitha Naveen for providing the data on compensation incentives from Coles, Daniel and Naveen (2006).

To estimate equation (2) we follow the approach proposed by Abowd et al. (2002) and start by forming groups of connected managers and firms.[9] Within these groups of connected managers we can identify manager and firm effects. In the first step, we construct the mean discretionary provision of all executives to obtain the executives' average discretionary loan loss provision $\overline{Y_i}$. In the second step, we subtract this average from equation (1) to wipe out the executive fixed effect. By using the information of the moving managers it is now possible to identify the firm fixed effects using ordinary least squares. Finally, the manager fixed effect can be recovered with the information about the firm fixed effect.[10] The resulting fixed effects are unbiased, whereas the time-varying estimates are unbiased and consistent (e.g., Wooldridge, 2010). Furthermore, because fixed effects are computed relative to a within-group benchmark, we normalize the fixed effects to make them comparable across groups following the procedure from Graham et al. (2012).

To obtain accurate estimates for the manager and firm fixed effects, a certain degree of mobility is necessary to avoid an estimation bias (Andrews, 2008; Gormley and Matsa, 2014). Mobility appears to be relatively high in our sample when compared to other studies. Table 1.1 documents that 10.76% (98 out of 911) of the managers change employers at least once, compared to 4.91% movers in Graham et al., (2012) or 4.56% in Hagendorff et al., (2019).

9 This works as follows: We start with an arbitrarily chosen manager and include all banks this manager worked for. In the second step, all managers who worked for these banks are included. This procedure is repeated until no more managers or banks can be added to the group. We start over with the next group until all data is exploited. This algorithm results in groups of connected executives and banks. Abowd, Creecy and Kramarz (2002) formally prove that connectedness is necessary and sufficient for identification of worker and firm fixed effects.

10 More detailed information on the exact calculation can be found in Graham et al. (2012) or Liu, Mao and Tan (2016)

Table 1.1 Manager mobility and connectedness

Panel A: Number of movers out of all managers

Mover	# Of firms in which managers have been employed	#Managers	%	Cum.
No	1	813	89.24	89.24
Yes	2	96	10.54	99.78
	3	2	0.22	100
	Total	911	100.00	-

Panel B: Groups of connected banks

Group	Manager-years	#Managers	#Movers	#Banks
1	33	13	1	2
2	1,451	299	41	33
3	603	93	14	13
4	137	18	1	2
5	133	26	2	3
6	33	11	1	2
7	403	76	7	8
8	50	9	1	2
9	101	14	1	2
10	192	43	5	5
11	133	19	1	2
12	106	18	2	2
13	115	27	2	3
14	109	19	2	2
15	171	37	4	4
16	59	17	1	2
17	41	5	1	2
18	72	8	1	2
19	59	12	1	2
20	137	31	2	3
21	129	16	1	2
22	96	23	1	2
23	112	26	2	2
24	120	16	1	2
25	72	22	1	2
26	73	13	1	2
Total	4,740	911	98	108

Table 1.1 provides summary statistics about the mobility of managers in the sample. Panel A indicates how many managers moved between banks. Panel B shows the groups formed using the AKM method to identify the manager fixed effects. All banks and managers within a certain group are connected by at least one moving manager.

Using the 98 moving managers, we are able to form 26 groups including all connected managers and banks. The largest connected group consists out of 33 banks including 299 managers. This illustrates the main advantage of the AKM method: a large amount of connectedness out of a relatively low amount of mobility (Abowd et al., 2002).

Table 1.2 presents descriptive statistics for manager and firm characteristics and compares the full sample (including all banks where we can obtain manager information) with the *AKM connectedness sample* and the *Mover sample* that includes only managers who switch their employer at least once during the sample period. The average manager in the AKM sample is 54.29 years old and works 5.48 years with each bank. An average tenure of 5 years should suffice for top managers to affect banks' accounting decisions. The observable executive characteristics in the full sample are, with an average executive's age of 53.83 and a tenure of 4.48 years, comparable, but still statistically significantly different at the 1% level. In addition, managers in the AKM sample receive a slightly higher salary (6.04 vs. 5.83, $p<0.01$) but a slightly lower bonus (3.36 vs. 3.76, $p<0.01$) compared to the full sample which relates potentially to the slightly larger size of AKM sample banks versus banks in the full sample (9.98 vs 9.82, $p<0.01$). However, risk taking incentives are fairly similar with an insignificant difference in compensation Delta and a difference in compensation Vega of -0.12 ($p<0.05$) between full and AKM sample. When comparing the AKM connectedness sample to the mover sample, we document that managers within the mover sample are on average 1.55 years younger ($p<0.01$) receive higher salaries and bonuses.

Table 1.2 Summary statistics and sample representativeness

	(1) All ExecuComp Banks		(2) AKM Connectedness Sample					(3) Mover Sample		Difference (1)-(2)	Difference (2)-(3)
Panel A: Manger Characteristics: Continuous Variables	N	Mean	N	Mean	SD	Min	Max	N	Mean		
Age	7667	53.83	4740	54.29	6.72	33	84	780	52.73	-0.45***	1.55***
Tenure	9893	4.48	4740	5.48	3.83	1	23	780	4.66	-1.01***	0.82***
Salary	9881	5.83	4735	6.04	0.56	3.29	8.91	777	6.18	-0.22***	-0.14***
Bonus	9893	3.76	4740	3.36	3.02	-4.61	9.95	780	3.81	0.40***	-0.46***
Delta	7813	-2.35	4740	-2.38	1.42	-14.21	7.2	780	-2.30	0.03	-0.08
Vega	8355	-3.57	4740	-3.45	2.2	-50.77	5.75	780	-3.29	-0.12**	-0.16*
Overconfidence	9108	0.172	4740	0.153	0.36	0	1	780	0.158	0.01***	-0.01

Panel B: Manager Characteristics: Categorical Variables

Variable	N	Mean	N	Mean	SD	Median		N	Mean		
CEO	9893	0.26	4740	0.33	0.47	0		780	0.46	-0.07***	-0.13***
CFO	9893	0.09	4740	0.11	0.31	0		780	0.10	-0.02***	0.01
Top Executive	9893	0.08	4740	0.10	0.30	0		780	0.08	-0.02***	0.02*
Male Indicator	9893	0.94	4740	0.93	0.25	1		780	0.94	0.00	-0.01
High Education (PhD, MBA, CPA)	9893	0.07	4740	0.10	0.30	0		780	0.17	-0.03***	-0.07***
Recession Executive	9893	0.10	4740	0.13	0.34	0		780	0.13	-0.03***	0.00

Panel C: Firm Characteristics: Continuous Variables

Variable	N	Mean	N	Mean	SD	Min	Max	N	Mean		
Mtb	9416	1.88	4740	1.72	0.87	-3.12	6.64	780	1.79	0.17***	-0.07**
Regulatory Capital	8952	2.29	4740	2.30	0.29	-0.62	3.85	780	2.28	-0.01**	0.02**
Size	9821	9.82	4740	9.98	1.60	6.60	14.76	780	10.35	-0.16***	-0.36***
Signed DLLP	8480	0.05	4740	0.21	3.03	-7.57	26.09	780	0.36	-0.15***	-0.15
Unsigned DLLP	8480	-7.04	4740	-6.93	0.93	-10.51	-3.65	780	-6.96	-0.11***	0.03

Table 1.2 provides summary statistics of the (1) the full Execucomp-Compustat-CRSP-Boardex-banks matched sample and the (2) AKM connectedness sample (including all banks with at least one mover and all executives who worked for these banks), and (3) the mover sample including only executives who worked for at least two banks during the sample period. Panel A includes all continuous executive variables Panel B provides summary statistics for all categorical manager variables. Signed DLLP and Unsigned DLLP are the signed and the unsigned log-transformed residuals from equation (1) representing proxies for discretionary loan loss provisioning. All other variables are defined in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel B shows descriptive statistics for all categorical time-invariant manager variables. On average there are 33% CEOs, 11% CFOs and 10% other top-tier executives (e.g., CIO, COO, CRO) in the connectedness sample. 93% of the executives are male. Again, the full sample differs only slightly, whereas the mover sample records a significantly higher proportion of CEOs (46%) and more highly educated managers (13%).

Panel C shows descriptive statistics for bank level characteristics. Again, the connectedness sample is representative of the full sample, except that banks in the connectedness sample are somewhat bigger (9.98 vs. 9.82, p<0.01), have a slightly lower market-to-book ratio (1.72 vs. 1.88, p<0.01), and lower absolute discretionary loan loss provisions (-7.04 vs. -6.93, p<0.01). When comparing the AKM sample to the mover sample we find that banks in the mover sample are on average larger than AKM banks (10.35 vs. 9.98, p<0.01) and have a higher market-to-book ratio (1.72 vs. 1.79, p<0.01).

Overall, the AKM sample seems to be fairly representative of the full sample. However, the descriptive statistics indicate that particularly moving managers differ significantly in terms of age and compensation from non-movers. Furthermore, moving managers seem to work for bigger banks with higher market-to-book ratios. Therefore, relying solely on moving mangers could lead to different inferences that would potentially not be generalizable to the connectedness or the full sample.

1.5.2. *Results*

We start our individual manager analysis with descriptive pooled OLS regressions on discretionary loan loss provisions. We subsequently add compensation characteristics, observable manager attributes and firm fixed effects to the model in order to test whether these variables help in explaining variation in loan loss provisioning choice. Precisely, we estimate the following pooled OLS benchmark model:

$$(3)\ DLLP_{\mathrm{j},t} = X_{j,t}\beta + W_{j,t}\,\gamma + \mu_t + \varepsilon_{\mathrm{j},t}$$

$W_{j,t}$ represents time-varying firm and manager characteristics and includes the market-to-book ratio, size, regulatory capital, age and tenure. Furthermore, we include year fixed effects (μ_t). We then subsequently add categorical *Manager Attributes* (CEO, CFO, Top Executive, Male, High Education), *Compensation* (Salary, Bonus, Delta and Vega) and *Firm Fixed Effects*. We then compare how the inclusion of these sets of variables changes the adjusted R^2 of the model. However, we cannot add and consistently estimate manager fixed effects in this simple OLS model without applying the AKM sampling technique. That is, our first analyses are purely descriptive as we are likely capturing some unobserved manager heterogeneity in particularly when including firm fixed effects.

We start with a benchmark model including only time-varying firm characteristics and time fixed effects. This model explains approximately 23.7% (adjusted R^2) of the variation in discretionary loan loss provisions.

Table 1.3 Manager attributes, controls, fixed effects and the adjusted R^2

Panel A: Adjusted R^2 in regressions on DLLP

	Total Adj. R^2	Difference to Benchmark
1 Benchmark Model (Controls)	23.7%	-
2 Benchmark + Compensation	28.8%	+5.1%***
3 Benchmark + Manager Attributes	24.2%	+0.5%
4 Benchmark + Compensation + Manager Attributes	29.8%	+6.1%***
5 Benchmark + Compensation + Firm Fixed Effects	49.6%	+25.9%***

Panel B: Comparing different fixed effect structures in regressions on DLLP

	OLS	Firm FE	Manager FE	Mover Method	AKM
Regulatory Capital	0.158	-0.677	0.039	-3.121*	-0.065
	(0.23)	(-0.91)	(0.05)	(-1.91)	(-0.08)
Size	0.263***	-0.166	0.071	0.189	-0.012
	(3.40)	(-0.62)	(0.40)	(0.24)	(-0.03)
MtB	-0.148	-0.929***	-0.859***	-1.042**	-0.864***
	(-0.53)	(-3.68)	(-3.10)	(-2.45)	(-2.94)
Vega	-0.166**	-0.150**	-0.122	-0.226	-0.127
	(-2.12)	(-2.17)	(-1.63)	(-1.18)	(-1.54)
Delta	-0.468***	-0.346***	-0.633***	-0.404	-0.627***
	(-4.82)	(-3.67)	(-3.37)	(-1.27)	(-2.99)
Tenure	0.050*	0.054***	0.105***	0.004	0.073
	(1.78)	(2.68)	(2.76)	(0.06)	(1.15)
Age	0.011	0.013*	-0.034	0.220	-0.066
	(1.03)	(1.70)	(-0.33)	(0.41)	(-0.56)
N	4,740	4,740	4,740	780	4,740
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	No	Yes	Yes
Manager fixed effects	No	No	Yes	Yes	Yes
R^2	29.6%	51.4%	60.7%	69.3%	62.3%
Adj. R^2	29.2%	50.0%	51.0%	58.1%	51.9%

Panel A of Table 1.3 shows the adjusted R^2 for different regressions on signed discretionary loan loss provisions. The difference in R^2 relative to the benchmark model is based on the Vuong (1989) test, using robust standard errors clustered by bank (Wooldridge, 2010). The benchmark model regresses DLLP on a set of time-varying control variables: Regulatory Capital, Size and Market-to-Book ratio, Tenure, Age and time fixed effects from Table 1.2. Benchmark + Compensation adds Salary, Bonus, Delta and Vega to the explanatory variables of the benchmark model. Benchmark + Manager attributes adds all categorical manager variables: CEO, CFO, Other Top-Executive, Male, High Education to the benchmark model. Panel B reports coefficient estimates for regressions of signed discretionary loan loss provisions on time-varying firm and manager covariates using different fixed effect structures: without manager and firm fixed effects (OLS), including only firm fixed effects (Firm FE), including only manger fixed effects (Manager FE), a spell fixed effect for all executive-firm combinations (Spell FE), the Mover Method from Bertrand and Schoar (2003) including manager and firm fixed effects, and the AKM method including manager and firm fixed effects. All other variables a. t-statistics are based on robust standard errors clustered by bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Adding compensation incentives (Delta, Vega) increases the benchmark adjusted R^2 to 28.8% (+5.1%, $p<0.001$[11]), whereas adding observable manager characteristics instead (age, tenure, gender, occupation, education, recession) does not significantly change the benchmark model adjusted R^2 (+0.5%). Including both, compensation and manager characteristics, increases the adjusted R^2 to 29.8% (+6.1%, $p<0.001$). However, when we add firm fixed effects to the benchmark and compensation model this increases the adjusted R^2 to 49.6% (+25.9%, $p<0.001$) documenting a substantial impact of unobservable firm heterogeneity for loan loss provisions. Without taking the interrelation of firms and managers into account, these results could appear as indicator for a very low impact of observable manager characteristics on loan loss provisions compared with firm fixed effects. However, the stark impact of firm fixed effects rather highlights that it is important to tease out the proportion of the firm effect that is attributable to idiosyncratic manager differences.[12]

We continue in Table 1.3, Panel B with an evaluation of four different fixed effect structures for regressions of discretionary loan loss provisions on time-varying manager and firm characteristics (equation [2]). We start with a pooled OLS regression that includes only time fixed effects (adjusted R^2 29.2%). Adding firm fixed effects increases the adjusted R^2 to 50%. Adding manager fixed effects increases the adjusted R^2 by an additional 1% (unadjusted +9.3%) to 51%.

---

[11] The difference in R^2 relative to the benchmark model is based on the Vuong (1989) test, using robust standard errors clustered by bank (Wooldridge, 2010).

[12] Adding time-invariant manager characteristics to this specification is not possible in a meaningful way because many managers stay at the same firm and, unless the AKM or mover method is used to ensure the effects are identified, it is not possible to estimate the manager effect unbiased.

Table 1.4 Statistical and economic importance of manager fixed effects

Panel A: F-statistics to test the statistical significance of fixed effects (p-values in parentheses)

	AKM	Mover method (Bertrand & Schoar 2003)	Spell fixed effect	Manager fixed effects	Firm fixed effects	OLS
Firm and Manager FE	2.06*** (0.000)	3.48*** (0.000)	3.25*** (0.000)	-	-	-
Manager FE	1.71*** (0.001)	0.61 (0.998)	-	3.34*** (0.000)	-	-
Firm FE	3.32*** (0.000)	2.37*** (0.000)	-	-	18.73 (0.000)	-

Panel B: Comparing the economic significance across different estimation methods. Partial R^2 attributable to fixed effects and time-varying characteristics.

	AKM	Mover Method (Bertrand & Schoar 2003)	Spell fixed effect method	Manager fixed effects	Firm fixed effects	OLS
Number of manager FE estimated	911	97	-	911 (unidentified)	-	-
Partial R^2 explained by manager FE	19.10%	10.19%	-	30.10%	-	-
Partial R^2 explained by firm FE	11.86%	24.00%	-	-	21.80%	-
Partial R^2 explained by time-variant covariates	31.32%	35.00%	-	30.60%	29.61%	-
adj. total R^2	51.90%	58.10%	51.90%	51.01%	50.00%	29.2%

Panel C: Economic significance. Partial R^2 attributable to fixed effects and time-varying characteristics using only C-Level managers

	AKM	Mover method (Bertrand & Schoar 2003)	Spell fixed effect	Manager fixed effects	Firm fixed effects	OLS
Number of manager FE estimated	196	38	-	474 (unidentified)	-	-
Partial R^2 explained by manager FE	19.92%	39.42%	-	30.82%	-	-
Partial R^2 explained by firm FE	0.90%	0.58%	-	-	24.54%	-
Partial R^2 explained by time-variant covariates	39.08%	26.71%	-	29.36%	28.62%	-
adj. total R^2	48.16%	51.68%	-	51.64%	50.52	29.68%

Table 1.4 Panel A shows F-test statistics for manager and firm fixed effects form the regressions of signed discretionary accruals on time-varying control variables using different fixed effect structures (Table 1.3, Panel B). The F-statistics indicate if the firm and manager fixed effect are jointly or individually significantly different from zero. Critical values for the F-statistic are different across models due to different degrees of freedom. We provide the corresponding p-values in parentheses to ease interpretation. Panel B reports the R^2 decomposition from equation (3) to show how much of the variation in discretionary loan loss provisioning is explained by time-varying characteristics, firm fixed effects, and manager fixed effects for the different estimation methods. Details on the regression coefficient estimates are provided in Table 1.3, Panel B. The covariance is normalized by the variance of the dependent variable. The total R^2 corresponds to the regressions in Table 3, Panel B. Panel C repeats the estimation from Panel B using only C-level managers. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

When we employ the mover method and include time, firm, and manager fixed effects, the adjusted R^2 increases to 58.1%. Using the AKM method the adjusted R^2 is 51.9%. While the slight increase in the adjusted R^2 for the latter two models points at a high overlap between manager and firm effects, the majority of the increase in explanatory power is attenuated by the degrees of freedom adjustment for the high number of manager fixed effects that also results in large differences between raw R^2 and adjusted R^2. Overall, the five different fixed effect specifications indicate that idiosyncratic manager effects seem to add explanatory power to models of loan loss provisions.

In addition to the differences in explanatory power, the inference from the coefficient estimates varies across model specifications. Whereas the mover method regression suggests that only the market-to-book ratio has a significantly negative association with loan loss provisions, the AKM regression additionally documents a negative association between discretionary loan loss provisions and mangers' compensation Delta. These differences could either document a different relationship between compensation incentives in the two samples or simply be resulting from a much more restricted mover sample that includes only 780 observations compared to 4,740 observations within the AKM sample.

We proceed by documenting the statistical and economic significance of manager fixed effects from the different model specifications. Table 4, Panel A, provides F-statistics for manager fixed effects, firm fixed effects, and the combination of both. We find that employing the AKM method, all fixed effects are statistically significantly different from zero at the 1% level. When we employ the mover method, we document that manager fixed effects individually are not significantly different from zero. That is, relying on the mover method would lead to different conclusions about the statistical relevance of managers for discretionary loan loss provisions.

Given the statistical significance of manager fixed effects under the AKM method, we continue by exploring the relative economic importance of manager fixed effects for loan loss provisions. We use the following R^2 decomposition from Graham et al. (2012) to explore the partial explanatory power of manager relative to firm fixed effects and other time-varying covariates:

$$(4)\quad R^2 = \frac{cov(y_{jt}, \hat{y}_{jt})}{var(Ln(y_{jt}))} = \frac{cov(y_{jt}, X_{it}\hat{\beta} + W_{jt}\hat{\gamma} + \hat{\phi}_j + \hat{\theta}_i + \mu_t + \hat{\varepsilon}_{j,t})}{var(Ln(y_{jt}))} = \frac{cov(y_{jt}, X_{it}\hat{\beta} + W_{jt}\widehat{\gamma + \mu_t})}{var(Ln(y_{jt}))} +$$

$$\frac{cov(y_{jt}, \hat{\phi}_j)}{var(Ln(y_{jt}))} + \frac{cov(y_{jt}, \hat{\theta}_i)}{var(Ln(y_{jt}))} + \frac{cov(y_{jt}, \hat{\varepsilon}_{j,t})}{var(Ln(y_{jt}))}$$

In equation (4), we decompose the variation in discretionary loan loss provisions in its different components. In particular, we investigate the explanatory power of manager and firm fixed effects, covariates, and residuals for discretionary loan loss provisions by exploring the covariance between these three components with discretionary loan loss provisions, normalized by the variance of discretionary loan loss provisions. Therefore, $\frac{cov(y_{jt}, \hat{\theta}_i)}{var(Ln(y_{jt}))}$ represents the fraction in discretionary loan loss provisions that is explained by the manager fixed effect.

Table 1.4, Panel B, reports the partial explanatory power for manager and firm fixed effects, time-varying characteristics, and residuals. The results confirm our hypothesis that individual managers have a major influence on loan loss provisions. Employing the AKM method, we document that the 910 identified manager effects explain on average 19% of the variation in discretionary loan loss provisions whereas 12% of the variation is explained by firm fixed effects. When employing the mover method, we find corroborating evidence with manager fixed effects explaining 10.19% and firm fixed effects accounting for 24% of the variation in loan loss provisions. In the model employing only (unidentified) manager fixed effects, the manager fixed effects account for 30.10% of the variation in loss provisions, potentially picking up omitted firm characteristics. Overall, these findings document a substantial impact of managers on discretionary loan loss provisions. Furthermore, when we explore the underlying distribution of the manager fixed effects from the AKM estimation, we find that manager fixed effects are almost normally distributed showing a significant variation across managers (untabulated).

We next strengthen the robustness of our tests. Therefore, we explore whether the results are sensitive to the type of included bank managers by exploiting a subsample incorporating C-level managers only. Table 1.4, Panel C, documents that although the sample size is much smaller with 196 C-level managers, the explanatory power of manager fixed effects stays largely constant (partial R^2=19.92%) while the firm fixed effect is attenuated to less than 1% (total R^2=48.16%). To further strengthen the robustness of the manager fixed effect estimation, we rerun the AKM analysis with several additional restrictions in Table 1.5.

Prior studies examining manager fixed effects raise the concern that these effects are potentially driven by random events during executives' tenure (Bertrand and Schoar, 2003; Choi et al., 2015) or endogenous managerial turnover (Fee et al., 2013). Although, this would affect our results only if employer-employee matching is based on time-varying characteristics that are not included in the model specification, we address remaining concerns of endogenous sorting of managers and banks with a subsample analysis including only plausibly exogenous executive transitions (Fee et al., 2013). However, managers are replaced only in rare cases due to obvious exogenous reasons such as predecessor death. Following Custodio and Metzger (2014) we collect plausibly exogenous manager turnovers from retirements. We consider turnovers classified as "retirement" in ExecuComp or that happen at the age of 61 or older as routine turnovers that are more likely to be exogenous than a result of the bank replacing a manager in favor of hiring a manager with a certain loan loss provisioning style.

Table 1.5 Robustness tests: economic significance of manager fixed effects

	Number of manager FE	Partial R^2 explained by manager FE	F-test that manager FE=0 (p-value)	Partial R^2 explained by firm FE	F-test that firm FE=0 (p-value)	Partial R^2 explained by time-variant covariates	Adj. total R^2
Exogenous turnover sample	120	37.97%	(0.066)	4.93%	(0.113)	19.60%	50.94%
At least two movers per firm	805	18.08%	(0.025)	15.61%	(0.000)	26.29%	49.19%
Only the largest connected group	298	18.80%	(0.014)	19.86%	(0.006)	37.89%	68.86%
Sample split: 2001-2014	603	20.63%	(0.004)	14.54%	(0.000)	34.06%	59.65%
Excluding 2007/2008/2009	806	22.70%	(0.052)	12.99%	(0.000)	21.65%	43.23%

Table 1.5 reports the R^2 decomposition from equation (3) for AKM regressions of discretionary loan loss provisions on time varying control variables (Regulatory Capital, Size, Market-to-Book ratio, Tenure, Age), time fixed effects, manager fixed effects, and firm fixed effects within five different samples. The table shows how much of the variation in signed discretionary loan loss provisions is explained manager fixed effects, firm fixed effects, and time-varying characteristics. The untabulated proportion is attributable to residuals. The F-test statistics indicate whether firm or manager fixed effect are statistically significantly different from zero. Critical values for the F-statistic are different across models due to different degrees of freedom. We provide the corresponding p-values in parentheses.

Table 1.5 documents the robustness of our findings to this more restrictive sample selection. Although we can only identify 120 of such plausibly exogenous turnovers, the partial explanatory power of manager fixed effects for discretionary loss provisioning increases to 38% (p-value<0.1), whereas firm fixed become statistically insignificant. Therefore, the inference from plausibly exogenous turnovers supports our prior finding that managers explain a substantial proportion of the variation in discretionary loan loss provisions, alleviating endogeneity concerns.

We perform four additional robustness tests with different subsamples. First, we ensure the consistency of our manager fixed effect estimates by including only firms with at least two movers per bank, and using only the largest connected group for the estimation. Second, we alleviate concerns that extreme events such as the financial crisis or duration of the sample period affect our results by first restricting the sample to the 2001-2014 period, and second, excluding the financial crisis years from 2007-2009. We continue to find that manager fixed effects significantly affect bank's loan loss provisioning in all robustness tests, although the economic magnitude of the manager effects varies slightly between 18% and 23% (p-value<0.01-0.052).

Overall, our results confirm that manager fixed effects play an economically and statistically significant role in explaining discretionary loan loss provisioning with a partial explanatory power of approximately 19%. In comparison, time-invariant bank characteristics explain on average 12% of the variation in discretionary loan loss provisions while further 31% of the variation are explained by control variables[13].

[13] The remaining proportion is not explained, therefore reflects the partial explanatory power of residuals. The high explanatory power of control variables is partly attributable to time fixed effects, added to the time-varying controls category to avoid overcategorization.

1.6. Management styles and the LLP choice

1.6.1. Research design

In the next step of our analysis, we explore whether bank manager's decision making affects various bank policy choices in a systematically related way. We start by investigating whether bank managers fixed effects explain variation for other bank policy choices beyond loan loss provisions. Specifically, we estimate equation (2) using manager's compensation incentives, and loan portfolio choices as dependent variables. We employ *Vega*, *Delta*, and total *Pay* as dependent variables in equation (2) to capture manger's intrinsic talent and their risk-preferences from their market-based compensation (Graham et al., 2012; Albuquerque et al., 2013; Francis et al., 2015). Furthermore, we capture manager's idiosyncratic influence on the loan portfolio employing the Loan-to-Deposit ratio (*LtD*), the ratio of non-performing loans to gross loans (*NPL*) and the ratio of loans to total assets (*Loans*). Banks with a higher proportion of loans naturally own less securities, and usually follow a more traditional banking business model (Beltratti and Stulz, 2012). Furthermore, *LtD* captures whether loans are funded with deposits or other potentially riskier sources of funding (Laeven and Levine, 2009). The non-performing loan ratio captures bank's non-performing loan classifications as a third important loan portfolio characteristic (Ghosh, 2015). We employ the AKM method to estimate the manager fixed effects for these six additional policy choices and to determine how much of the variation is explained by mangers idiosyncratic influence.

In the next step, we explore whether we find significant correlations across these individual manager styles for certain bank outcomes. For example, do managers that exert a high influence over banks loan loss provision also affect non-performing loan classifications? Or do managers with a higher preference for risk-incentivized compensation also express a preference for more discretionary loan loss provisions? We analyze the correlation structure between manager fixed effects in the to answer these questions. We then investigate whether individual observable characteristics explain manager fixed effects and whether we find overarching patterns how observable manager characteristics influence managerial styles. While many time-invariant characteristics such as ability, talent or personality are likely difficult to quantify, exploring which observable factors play a role for bank manager's accounting and policy decisions is key to the enhance the understanding of the role of manager characteristics for accounting decisions.[14] Therefore, we estimate the following cross-sectional regressions to test the influence of observable manager characteristics for the accounting and policy choices:

$$(4)\ Manager\ FE_{i,k} = Manager\ Characteristics_{i,}\beta + \phi_k + \varepsilon_{\mathrm{i,k}}$$

Where i denotes managers and k denotes the AKM estimation group in which we estimated the manager effect. $Manager\ FE_{i,k}$ is the manager fixed effect from the eight different AKM regressions (equation 2), employing discretionary loan loss provisions (signed and unsigned), Vega, Delta, Total Pay, Loans, Loans-to-Deposits, and Non-Performing Loans as dependent variables.[15] *Manager Characteristics* includes demographic variables (Male, Recession Executive), occupational status (CEO, CFO, Top Executive), education (Higher Education), and average risk-taking incentives (Average Delta, Average Vega, Overconfident). In addition, we add AKM estimation group fixed effects (ϕ_k) to account for differences in the estimation group. This is appropriate because manager fixed effects are estimated within groups of connected managers

[14] Graham and Liu (2012) interpret manager fixed effects with management ability and talent, but note that manger fixed effects capture also all other time-invariant individual attributes.

[15] All Variables are defined in Appendix A.

and banks and are always estimated relative to the within group before we normalize them. In addition, we cluster standard errors on the bank level to account for any correlations in managerial characteristics at the bank level.

Male is an indicator variable that takes the value of one for managers that are male. Evidence on the influence of gender on corporate decision making is mixed. While Ge et al. (2011) do not find a significant relation between gender and earnings management, Huang and Kisgen (2013) document that female executives are more likely to make risky and overconfident corporate decisions. In contrast, Francis et al. (2015) find that female CFOs tend to increase accounting conservatism compared to their male peers. Given the mixed evidence on the influence of gender on accrual quality, we make no ex ante prediction about the influence of gender on loan loss provisions.

Recession Executive is a binary variable that takes the value of one if the manager started her career during a NBER-defined recession. Schoar and Zuo (2017) document that an executive's management style depends significantly on the market conditions present when the executive enters the labor market. Their results indicate that CEOs who enter the labor market during a recession exert a conservative management style with respect to R&D expenditures, capital expenditures and leverage. Because the career start date is endogenously determined and affected by economic cycles, we follow their methodology to identify recession executives. First, we add 24 years, the average age of starting to work at the first position, to the executives' birth date. Second, we classify an executive's first year on the labor market as recession year if it falls at least six months into a National Bureau of Economic Research-defined recession.

In addition, we include binary indicator variables for the exact occupation of the manager denoting whether the manager is either a *CEO*, *a CFO* or another C-level *Top Executive*. While it is ex-ante unclear whether CEOs, CFOs or other top executives have the greatest impact on loan loss provisions, prior literature suggests that CFOs play an incremental role for earnings management in non-banks (Jiang et al., 2010).

To test if education explains variation in managers' fixed effects, we collect the highest degree of the executive and create a binary indicator variable (*Higher Education*) that takes the value of one for all managers that have a PhD, MBA or CPA qualification. Education is frequently employed as a proxy for talent among workers (e.g. Abowd et al., 1999). Furthermore, Bertrand and Schoar (2003) document a positive impact of managers with MBA qualification on corporate performance. Nevertheless, prior evidence from Ge et al. (2011) indicates that having a MBA or CPA qualification does not significantly affect accounting styles in non-banks.

Furthermore, we proxy for managers' risk-taking incentives using managers average equity compensation (*average Vega* and *average Delta*) incentives over her career. While Vega theoretically provides clear risk-taking incentives, option Delta has two countervailing effects (Armstrong et al., 2013). On the one hand, delta incentives risk-taking by rewarding managers with wealth increases if the stock price accelerates. On the other hand, a higher Delta simultaneously exposes managers' wealth to a higher stock-price risk which should reduce risk-taking. Important to note here is that we use manager's average Delta and Vega over their whole sample period while we tease out the time-varying effect of both variables within the AKM estimation.

We include *overconfidence* as an additional proxy for managers risk-taking incentives. We employ a binary indicator variable that takes the value of one for managers who do not exercise stock options that are more than 67% in the money (Campbell et al., 2011). Overconfident executives are associated with overly optimistic forecasts (Hribar and Yang, 2016) and have a higher likelihood of intentional misstatements (Schrand and Zechman, 2012).

1.6.2. Results

We first document that managers impose a significant influence over all examined corporate decisions. Table 1.6, Panel A, shows that manager fixed effects explain between 11.26% and 50.28% of the variation in managements' policy and accounting styles. Managers fixed effects seem to matter in particular for compensation and loan portfolio choices. In the next step, we analyze the correlations across the manager effects for the different corporate decisions. Panel B reports the pairwise correlations documenting that loan loss provisioning styles are highly correlated with managements' idiosyncratic preferences for compensation-based risk-taking incentives (Vega, Delta, Total Pay) and non-performing loan classifications. This indicates that a manager's loan loss provisioning style is associated with preferences for other important corporate policy choices.

Along these lines, we explore in Panel C whether the correlation in management styles across different corporate decisions is also reflected in observable manager characteristics that are captured in the manager fixed effects. To test whether observable manager characteristics affect corporate choices in a systematic way we regress the manager fixed effects for the corporate choice on different (time-invariant) observable individual characteristics capturing demographics, occupational status, education and risk-taking incentives.

Table 1.6 Correlation across management styles and individual characteristics

Panel A: Economic significance of fixed effects and time-varying characteristics for bank policy choices

	Unsigned DLLP	Signed DLLP	Vega	Delta	Pay	Loans	LtD	NPL
Number of manager FE estimated	911	911	931	931	931	931	931	916
Partial R^2 explained by manager FE	**11.26%**	**19.10%**	**19.45%**	**46.54%**	**48.81%**	**50.28%**	**44.35%**	**12.68%**
Partial R^2 explained by firm FE	13.83%	11.86%	2.54%	4.65%	4.37%	26.77%	42.82	6.99%
Partial R^2 explained by time-variant covariates	35.66%	31.32%	35.66%	35.89%	35.72%	11.58%	0.27%	58.43%
adj. total R^2	49.98%	51.90%	46.16%	83.23%	85.58%	85.54%	83.68%	71.59

Panel B: Pairwise correlations across different management styles

	Unsigned DLLP FE	Signed DLLP FE	Vega FE	Delta FE	Pay FE	Loans Fe	LtD FE	NPL FE
Unsigned DLLP FE	1.0000							
Signed DLLP FE	0.5124*	1.0000						
Vega FE	0.0365*	0.1781*	1.0000					
Delta FE	0.2605*	0.3587*	0.5656*	1.0000				
Pay FE	0.2594*	0.3222*	-0.0281	0.1724*	1.0000			
Loans Fe	-0.1852*	0.0053	0.2041*	0.0757*	-0.1784*	1.0000		
LtD FE	0.0577*	-0.1228*	0.1014*	0.1234*	-0.0577*	0.6150*	1.0000	
NPL FE	0.5040*	0.7373*	0.0517*	0.3764*	0.4979*	-0.2108*	-0.1031*	1.0000

Table 1.6 (continued)

Panel C: Individual characteristics and management styles

	Unsigned DLLP FE	Signed DLLP FE	Vega FE	Delta FE	Pay FE	Loans Fe	LtD FE	NPL FE
Demographics								
Male	0.043	0.400	0.889**	0.377*	0.035	-0.000	0.022	0.005***
	(0.516)	(0.247)	(0.011)	(0.088)	(0.631)	(0.981)	(0.102)	(0.006)
Recession Executive	-0.001	-0.098	-0.051	-0.047	-0.036	-0.000	-0.000	0.001
	(0.984)	(0.633)	(0.861)	(0.778)	(0.630)	(0.944)	(0.970)	(0.512)
Occupational Status								
CEO	0.118***	0.248*	-0.040	0.102	0.581***	-0.002	0.001	0.002*
	(0.000)	(0.054)	(0.850)	(0.265)	(0.000)	(0.685)	(0.873)	(0.078)
CFO	-0.005	-0.501**	-0.550*	-0.337*	-0.230***	-0.007	-0.028***	-0.006***
	(0.922)	(0.016)	(0.067)	(0.074)	(0.000)	(0.316)	(0.010)	(0.000)
Top Executive	-0.053	-0.352	-0.608**	-0.222	0.076	-0.007	-0.017	-0.003*
	(0.389)	(0.185)	(0.032)	(0.128)	(0.329)	(0.393)	(0.153)	(0.086)
Education								
Higher Education (PhD, MBA, CPA)	-0.034	-0.219	-0.345	-0.177	-0.016	-0.002	-0.016	-0.003*
	(0.480)	(0.179)	(0.174)	(0.165)	(0.834)	(0.803)	(0.174)	(0.069)
Risk-Taking Incentives								
Average Delta	0.059***	0.466***	0.232	0.803***	0.136***	-0.007*	0.010	0.006***
	(0.010)	(0.000)	(0.201)	(0.000)	(0.002)	(0.077)	(0.125)	(0.000)
Average Vega	-0.046**	-0.182*	0.447***	-0.167***	-0.045	-0.006*	-0.004	-0.002**
	(0.044)	(0.056)	(0.002)	(0.005)	(0.126)	(0.074)	(0.327)	(0.029)
Overconfidence	0.086	0.553**	0.680***	0.050	0.208***	0.007	0.021	0.004***
	(0.149)	(0.029)	(0.004)	(0.546)	(0.009)	(0.441)	(0.147)	(0.002)
N	4729	4729	4729	4729	4729	4729	4729	4729
Adj. R^2	26.7%	29.1%	18.3%	38.5%	34.4%	39.0%	70.3%	40.5%
Fixed Effects	26.4%	29.0%	18.3%	38.5%	33.8%	83.8%	69.1%	40.5%
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Panel A of Table 1.6 reports the R^2 decomposition from equation (3) and shows how much of the variation in bank policy choices is explained by manager fixed effects, firm fixed effects, time-varying characteristics, and residuals. We use the AKM method and regress each policy choice on time-varying firm and manager covariates (regulatory capital, market-to-book-ratio, size, age, tenure) with time, firm and manager fixed effects. Due to high multicollinearity, we exclude age in the Pay, LtD, and NPL regressions. We investigate the following policy choices: unsigned and signed DLLP as proxies for discretionary loan loss provisions. Vega, Delta and Pay (total compensation) as compensation choices. Loans, loans-to-deposits (LtD) and non-performing loans (NPL) as banks strategic choices. All variables are defined in Appendix A. Panel B reports pairwise correlations across manager fixed effects (management styles) for the different bank policy choices from Panel A. Panel C investigates the determinants of manager fixed effects by regressing manger fixed (as estimated in Panel A) on different observable time-invariant manager characteristics. P-values are based on robust standard errors clustered by bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

We find no significant association between managers' gender, education, prior crisis experience and loan loss provisioning styles. However, male managers seem to express a preference for more risk-taking in the form of higher compensation Vega and Delta. Although consistent with prior evidence, given the relatively low number of female managers in our dataset, this finding is not necessarily generalizable to all female managers.

Furthermore, our results suggest that the manager's exact occupation matters. We document that CEOs impose the highest influence over (absolute unsigned) loan loss provisions. In addition, we find that CEOs on average manage loan loss provisions upward whereas CFOs have an opposing negative influence on provisions. This finding extends prior evidence documenting that CFOs play an incremental role for earnings management (Jiang et al. 2010). When exploring other management decisions, we find CEOs to exert more influence over their total pay and non-performing loans while CFOs have on average significantly lower individual effects on compensation and loan portfolio characteristics such as loan-to-deposits and non-performing loan classifications.

Individual risk-taking incentives also affect provisioning styles and loan portfolio choices significantly. Manager's average compensation Vega and Delta are also significantly correlated with manager's influence on loan loss provisions. Mangers with higher *Average Delta* exert a larger idiosyncratic influence on loss provisions whereas managers with higher average Vegas manage loan loss provisions less. However, managers with higher average compensation Vega on average influence the loan loss provision downwards. Because we tease out the time-varying effect of compensation incentives in the AKM regression already, the manager fixed effects capture only the part of the compensation incentives that relates to manager's inherent preferences. Along these lines, we document a preference for a lower loan ratio for managers with high Vega and a less loans classified as non-performing for managers with high Delta. In addition, we do not document an effect of overconfident managers for absolute loan loss provisions whereas we find that overconfident managers on average significantly increase loan loss provisions.

Although these results indicate that observable characteristics matter, the correlation of observable manager characteristics across the different accounting and policy decisions appears to be little systematic. One potential explanation for this relatively unsystematic correlation is that observable manager characteristics are unlikely to manifest themselves in isolation and are often highly correlated. For instance, the choice of the highest degree of an executive is potentially highly correlated with other executive traits such as intelligence, ability or overconfidence. Therefore, we employ a Principal Component Analysis (PCA) in the next step of our analysis to build a composite score capturing the main dimensions of all observable manager characteristics. Because most characteristics are captured in binary variables, we use polychoric correlations for the PCA.

The PCA in Table 1.7, Panel A encompasses all manager characteristics from Table 1.6 and identifies five components with eigenvalues larger than one (Kaiser criterion). In addition, we build a composite PCA score from these five components that intends to capture a major part of the variation in observable manager characteristics. We document substantial variation in component scores for the individual variables across the different components indicating a successful variance reduction. In Table 1.7, Panel B, we then substitute the individual characteristics from equation (4) with the five individual PCA components to investigate whether the combined variation from observable characteristics explains managerial styles for different policy choices in a systematically related way. The individual PCA components and the composite PCA score are significantly associated with the manager fixed effect for the different bank policy choices and banks loan loss provisions. Furthermore, we find overarching patterns for the PCA components and the combined PCA score across the different management styles. This finding is consistent with the idea that although individual observable characteristics do not explain a large fraction of the variation in individual manager styles, in combination they are still meaningfully and systematically correlated with several accounting and policy outcomes.

In the next step, we build on our findings from the prior analyses that latent managerial styles appear to influence an array of corporate decisions in an interrelated way by constructing manager profiles based on their revealed individual preferences for the eight different policy choices. We cluster managers according to their manager fixed effects for the eight corporate accounting and policy choices to determine a set of unique manager profiles. Using cluster analysis has the advantage of minimizing variance within clusters while maximizing the variance between clusters. Specifically, we employ a k-means clustering analysis using the Calinski and Harabasz (1974) index to determine the number of clusters. We label the groups according to the classification in Pitcher and Smith (2001) into 'technocrats', 'artists', 'craftsmen', and 'traditionalists'.

Table 1.7 Cross-sectional variation of manager fixed effects

Panel A: PCA descriptive statistics

Components	Eigenvalue	Difference	Proportion	Cumulative
Component 1	2.813	1.494	0.281	0.281
Component 2	1.319	0.108	0.132	0.413
Component 3	1.211	0.071	0.121	0.534
Component 4	1.139	0.067	0.114	0.648
Component 5	1.072	0.164	0.107	0.755
Component 6	0.908	0.073	0.091	0.846
Component 7	0.835	0.418	0.084	0.930
Component 8	0.417	0.213	0.042	0.971
Component 9	0.204	0.123	0.020	0.992
Component 10	0.081	-	0.008	1.000

Variable	Component 1	Component 2	Component 3	Component 4
CEO	0.469	0.152	-0.243	-0.429
CFO	-0.325	0.384	0.482	0.270
Top Executive	-0.099	-0.705	0.085	0.356
Male	0.136	0.412	0.390	0.029
Lower Education (Graduated)	0.482	-0.158	0.259	0.011
High Education (PhD, MBA, CPA)	0.416	-0.130	0.473	0.177
Recession Executive	0.207	-0.055	0.266	-0.145
Delta (Mean)	0.369	0.161	-0.260	0.445
Vega (Mean)	0.213	-0.123	-0.045	0.146
Overconfidence	0.131	0.279	-0.344	0.586

Table 1.7 (continued)

Panel B: PCA Components and Management Styles

	Unsigned DLLP FE	Signed DLLP FE	Vega FE	Delta FE	Pay FE	Loans FE	LtD FE	NPL FE
Component 1	0.039***	0.262***	0.332***	0.370***	0.199***	-0.005***	0.006*	0.003***
	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.074)	(0.000)
Component 2	0.051***	0.243***	0.173**	0.208***	0.051**	0.002	0.008**	0.002***
	(0.002)	(0.001)	(0.012)	(0.000)	(0.019)	(0.472)	(0.033)	(0.000)
Component 3	-0.041**	-0.307***	-0.246***	-0.283***	-0.152***	-0.000	-0.010***	-0.003***
	(0.013)	(0.000)	(0.006)	(0.000)	(0.000)	(0.883)	(0.003)	(0.000)
Component 4	0.007	0.172**	0.283**	0.264***	-0.011	-0.004*	0.004	0.002***
	(0.728)	(0.028)	(0.041)	(0.000)	(0.730)	(0.100)	(0.416)	(0.003)
Component 5	-0.045	-0.146	0.489**	0.103	-0.056	-0.011**	-0.006	-0.001
	(0.170)	(0.386)	(0.015)	(0.261)	(0.265)	(0.022)	(0.411)	(0.346)
N	4729	4729	4729	4729	4729	4729	4729	4729
Adj. R^2	25.9%	27.8%	16.8%	28.8%	31.9%	39.1%	70.1%	36.6%
Fixed Effect	Group	Group	Group	Group	Group	Group	Group	Group
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Panel C: PCA Scores and Management Styles

	Unsigned DLLP FE	Signed DLLP FE	Vega FE	Delta FE	Pay FE	Loan FE	LTD FE	NPL FE
PCA Score	0.062*	0.438**	0.750***	0.713***	0.291***	-0.012***	0.008	0.005***
	(0.055)	(0.013)	(0.000)	(0.000)	(0.000)	(0.004)	(0.266)	(0.000)
N	4729	4729	4729	4729	4729	4729	4729	4729
Adj. R^2	23.8%	23.4%	11.7%	19.2%	22.3%	37.8%	69.4%	29.2%
Fixed Effect	Group	Group	Group	Group	Group	Group	Group	Group
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Panel A of Table 1.7 shows descriptive statistics for a principle components analysis on all time-invariant manager attributes from Table 1.6 (Male, Recession Executive, CEO, CFO, Top Executive, Higher Education, Average Vega, Average Delta, Overconfidence). We use polychoric correlations due to many binary input variables to perform the principle component analysis. Panel B shows regressions of manager fixed effects for different bank policy choices on the five different principal components that capture variation of the individual characteristics from Panel A. We employ the Kaiser criterion (Eigenvalue>1) as cut-off for significant components to retain. Panel C aggregates the five components from Panel C in one principal component score. P-values are based on robust standard errors clustered by bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

In Table 1.8, we descriptively explore the differences in observable manager characteristics for the four manager clusters. We find that managers labeled as traditionalist are on average younger, less likely to be overconfident, and have low risk-taking incentives from compensation, whereas managers labeled as artists are more likely to be overconfident, are more often highly educated, and have the highest compensation risk-taking incentives. As expected there is significant variation across manager clusters in the combined PCA score that combines all observable manager differences.

Table 1.8 Manager profiles

	Technocrats	Artists	Craftsmen	Traditionalists
#Managers	253	182	329	147
Manager Characteristics				
CEO	0.366	0.446	0.271	0.233
CFO	0.073	0.049	0.151	0.155
Top Executive	0.074	0.069	0.113	0.171
Male	0.914	0.974	0.938	0.888
High Education (PhD, MBA, CPA)	0.109	0.128	0.074	0.101
Recession Executive	0.154	0.136	0.111	0.120
Delta (Mean)	-2.394	-1.644	-2.599	-3.084
Vega (Mean)	-3.554	-3.003	-3.375	-4.274
Overconfidence	0.148	0.230	0.137	0.067
Mean PCA Score	0.151	0.459	0.031	-0.302
Age	54.834	56.836	53.017	52.257
Tenure	4.750	6.234	5.780	4.685

Table 1.8 provides summary statistics of the different manager profiles. Manager profiles are determined using a k-means clustering on all different management fixed effects from Table 6 (DLLP FE, Vega FE, Delta FE, Pay FE, Loans FE, LtD FE, NPL FE). The optimal number of clusters is determined by the Calinski and Harabasz (1974) index. Mean PCA score is the average PCA score from Table 1.7, Panel C. All other variables are defined in Appendix A.

1.7. Interaction with team composition

1.7.1. Research design

In the following section we investigate whether top management team composition matters for bank's loan loss provisioning decisions and how it interacts with individual management styles. Specifically, we explore whether different manager types influence the bank's accounting choices and how the effect is altered by heterogeneity at the top management team level. Therefore, we estimate the following model:

$$(5)\ Policy\ Choice_{i,j,t} = Manager\ Type_{i,j,t}\beta + Diverse\ TMT_{j,t}\gamma + Diverse\ TMT_{j,t} * Manager\ Type\phi_{i,j,t} + \theta_i + \mu_t + \phi_j + \varepsilon_{i,j,t}$$

As dependent variable we use all accounting and corporate policy choices from Table 6, Panel A. Therefore, the dependent variable is the time-varying corporate choice. $Manager\ Type_{i,j,t}$ denotes and indicator variable for the four unique manager types we identify in the cluster analysis from Table 8. Managers labeled as 'Traditionalist' serve as the reference group in all tests. We include a binary variable $Diverse\ TMT_{j,t}$ that indicates whether at least two different manager types (Technocrat, Artist, Craftsmen or Traditionalist) are represented in the top management team. Furthermore, we include size, regulatory capital, and the market-to-book ratio to capture time-varying firm characteristics. In addition, we include firm- and year-fixed effects to account for unobserved heterogeneity on the year and bank level. In all our tests, we draw statistical inferences based on standard errors clustered by bank to control for time-series correlation (Petersen, 2009).

1.7.2. Results

We report the results for the impact of different manager types and top management team heterogeneity in Table 1.9. Managers that we label as artists and technocrats exert on average a higher discretion over the loan loss provision after controlling for bank characteristics, year, and bank fixed effects. Furthermore, artist managers are also associated with a preference for higher risk-taking incentives from compensation (Vega). In addition, we document a positive baseline effect of *Diverse TMT*. That is, team diversity does not seem to be associated with less discretionary loss provisions per se. However, diversity is on average rather associated with overprovisioning than with risky underprovisioning. Furthermore, we document that top management team diversity can attenuate the negative effect of technocrats and artists on loan loss provision quality. This beneficial effect of top management team diversity is particularly pronounced in teams that include risk-seeking managers that we label as artists. Overall, our results document that diversity within top management teams can moderate the significant association between individual manager styles and the level of reporting discretion. Therefore, top management team diversity can help reducing reporting discretion for manager types that are most prone to making risky provisioning and loan portfolio decisions.

Table 1.9 Top management team composition and bank outcomes

	Unsigned DLLP	Signed DLLP	Vega	Delta	Pay	Loans	LtD	NPL
Technocrats	0.555***	3.607**	4.682	1.362***	0.191	0.109***	0.142***	0.014
	(0.004)	(0.015)	(0.107)	(0.000)	(0.268)	(0.004)	(0.003)	(0.169)
Artists	0.572***	3.205**	6.433**	2.629***	0.259	0.025	0.022	0.012
	(0.006)	(0.022)	(0.030)	(0.000)	(0.205)	(0.401)	(0.654)	(0.263)
Craftsmen	0.134	1.138	5.586*	1.385***	0.055	-0.006	0.019	0.006
	(0.382)	(0.392)	(0.059)	(0.000)	(0.770)	(0.796)	(0.612)	(0.548)
TMT Diversity	0.308**	2.245*	2.997	0.293	-0.168	0.009	0.030	0.013
	(0.013)	(0.089)	(0.313)	(0.163)	(0.238)	(0.665)	(0.215)	(0.195)
Technocrat * Diverse TMT	-0.384**	-2.747*	-3.329	-0.213	0.126	-0.106***	-0.135***	-0.013
	(0.037)	(0.068)	(0.260)	(0.348)	(0.428)	(0.004)	(0.005)	(0.193)
Artist * Diverse TMT	-0.581***	-3.050**	-3.284	-0.438*	0.420**	-0.021	-0.017	-0.014
	(0.004)	(0.029)	(0.264)	(0.080)	(0.012)	(0.413)	(0.670)	(0.204)
Craftsmen * Diverse TMT	-0.132	-1.350	-3.329	-0.383	0.170	0.009	-0.012	-0.009
	(0.392)	(0.318)	(0.254)	(0.125)	(0.264)	(0.686)	(0.717)	(0.389)
Regulatory Capital	-0.230*	-1.044	0.642*	0.866***	0.200**	-0.063**	-0.050	-0.015***
	(0.073)	(0.162)	(0.074)	(0.000)	(0.018)	(0.021)	(0.179)	(0.000)
Size	-0.075	-0.352	0.814***	0.429***	0.346***	-0.026	0.053*	-0.005**
	(0.383)	(0.220)	(0.000)	(0.000)	(0.000)	(0.169)	(0.054)	(0.022)
MtB	-0.096*	-0.963***	0.034	0.242***	0.181***	-0.003	-0.010	-0.006***
	(0.099)	(0.000)	(0.795)	(0.005)	(0.000)	(0.785)	(0.487)	(0.000)
N	4729	4729	4729	4729	4729	4729	4729	4729
Adj. R^2	51.0%	49.0%	36.6%	57.3%	65.6%	77.5%	75.8%	65.6%
Firm & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 9 shows regressions of different bank policy choices on indicator variables for the different manager profiles. Technocrats, Artists, Craftsmen, and Traditionalists are indicator variables for different manager profiles from the k-means clustering in Panel A. Traditionalists serve as the reference group. The optimal number of clusters is determined by a k-means clustering and the Calinski and Harabasz (1974) index. Diverse TMT is a binary indicator variable that takes the value of one for a top management team that consist out of more than one particular manager type. P-values are based on robust standard errors clustered by bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

1.8. Conclusion

This study explores the role of manager characteristics and top management team composition for banks' loan loss provisions. While prior literature documents that bank-specific incentives and variation over time shape loan loss provisions, we are the first to show a significant idiosyncratic manager effect for this major accounting choice. Nevertheless, our tests reveal that observable compensation and manager characteristics explain only a small fraction of banks loan loss provisioning behavior. The low correlations between observable characteristics and reporting outcomes, however, do not imply that individual bank managers have little influence on accounting choices. Managers exert influence in an idiosyncratic way through their preferences, skills, or values that are inherently difficult to measure but important to understand a managers' role in the accounting process.

Exploiting a large sample of connected managers and banks, we document that after accounting for firm and time differences manager characteristics explain approximately 19% of the variation in the discretionary loan loss provision. We use plausibly exogenous turnovers as a setting to corroborate these findings and to document that manager fixed effects are not a mere outcome of firm policy changes. Furthermore, manager styles for different corporate policies are systematically correlated. For example, managers employing high discretion in the loan loss provisioning choice also prefer a higher level of risk-taking and, on average, a lower quality of the loan portfolio. That is, managers who have a distinct impact on the loan loss provisioning do exert their influence on other corporate actions in a systematically related way. Using these systematic correlations across manager styles we cluster managers into four unique types. We document that particularly managers whom we label as *artists* and *technocrats* use discretion over the loan loss provision. In addition to the individual manger effects we document that top management team composition can significantly alter the impact of individual managers. Our results provide evidence that top management team diversity mutes the idiosyncratic influence of managers that employ the most aggressive loan loss provisioning styles.

Overall, our findings imply that bank supervisor's focus on skills and qualifications of individual managers can be only partially justified by the relatively limited systematic impact that individual observable characteristics have on relevant corporate policies. However, the focus on individual managers is necessary as a large proportion of bank's policy choices is attributable to individual management styles. Furthermore, idiosyncratic manager influence seems to interact strongly with the combination of manager types within the top management team providing some support for regulation to increase the top management team diversity.

1.9. Appendix A: Variable definitions

Manager Variables	Description	Source and computation
Age	Executives' Age in years	ExecuComp
Tenure	Duration of the employment on the current position	ExecuComp
Male	Indicator variable for male managers	ExecuComp
Salary	Total fixed Salary	ExecuComp: Natural logarithm of fixed salary
Bonus	Bonus	ExecuComp: Natural logarithm of bonus
Total Pay	Total Salary and Bonus	Execucomp: Natural logarithm of total compensation
Vega	Dollar change in wealth linked to a 1% increase in stock return volatility	Coles, Daniel and Naveen (2006): Scaled with total cash compensation and log transformed (Edmans, 2009)
Delta	Dollar change in manager's wealth to changes in a bank's stock price performance	Coles, Daniel and Naveen (2006): Scaled with total cash compensation and log transformed (Edmans, 2009)
CEO	Indicator for manager's occupation	Execucomp/Boardex
CFO	Indicator for manager's occupation	Execucomp/Boardex
Top Executive	Indicator for manager's occupation	Execucomp/Boardex: Top 5 executive classified as CEO,CFO,CRO,CIO or COO
Recession Executive	Indicates managers that started their career during a recession	Execucompt Birthdate + 24 years within NBER-defined recession
Higher Education	Indicator variable for managers with PhD, CPA or MBA qualification	Boardex
Over-confidence	Indicator for overconfident managers	Indicator for unexercised stock options more than 67% in the money

Bank Variables	Description	Source and computation
MtB	Market to book ratio	Compustat: Market value of equity divided by the book value of equity(common shares outstanding*price/common equity)
Size	Size	Compustat: Natural logarithm of total assets
LLP	Loan loss provisions	Compustat: Loan loss provisions scaled by lagged total loans
Regulatory Capital	Tier 1 regulatory capital	Compustat: Natural logarithm of tier 1 capital
NPL	Non-performing loans	Compustat: Non-performing loans scaled by lagged total loans
CO	Charge-offs	Compustat: Charge-offs scaled by lagged total loans
ALW	Allowance for loan losses	Compustat: Loan loss allowance scaled by total loans
EBLLP	Earnings before loan loss provisions	Compustat: (Earnings + loan loss provisions) scaled by lagged total loans
LtD	Loans-to-Deposits	Compustat: Total loans scaled with total deposits
NPL	Non-performing loans ratio	Compustat: Non-performing loans scaled with total loans
Loans	Total loans ratio	Compustat: Total loans scaled with total assets
HPI	House price index	Federal Housing Finance Agency
GDP	Gross domestic product	Federal Reserve bank of St. Louis

Chapter 2

Do Supervisory Disclosures Lead to Greater Bank Transparency? The Role of Enforcement and Market Discipline

"One of the outcomes we expect from these tests is to dispel this fog that lies over bank balance sheets in the Euro area and in Europe."

Mario Draghi, 23/10/2013, in a speech to the European Parliament

2.1. Introduction

Supervisors can influence the reporting behavior of supervised firms through different channels. Their public enforcement relies on direct interventions such as comment letters, supervisory instructions, or fines (Jackson and Roe, 2009). However, they can also disclose private information to the public to increase market attention and encourage third-party monitoring (Duro, Heese, and Ormazabal, 2019). Such supervisory disclosures can also serve as a commitment device to assure supervisory discipline (Bushman and Williams, 2012; Dudley, 2009). In the banking industry, the role of supervisory disclosures about the financial health, risk, and transparency of regulated banks is controversial (Goldstein and Sapra, 2014). Enhanced disclosures equip market participants with a better understanding of bank fundamentals and thus help establish market discipline (Berger, Davies, and Flannery, 2000; Flannery, 2001; Herring, 2004), but increased transparency potentially mitigates opportunities for regulators to practice forbearance behind the scenes (Gallemore, 2019; Skinner, 2008). Therefore, ex ante it is not clear whether supervisory reporting preferences are in line with market demand for bank transparency, and how supervisory disclosures interact with traditional enforcement in increasing bank transparency.

The European Central Bank's (ECB) Asset Quality Review (AQR) provides a useful setting to explore the financial reporting preferences of bank regulators and the complementary roles of traditional enforcement and supervisory disclosures. In the run-up to the European Single Supervisory Mechanism (SSM), which shifted the responsibility for the prudential supervision of the most significant Eurozone banks from national regulators to the ECB, the ECB reassessed the audited financial statements of each affected bank and published its findings.[16] For example, the ECB revealed that it viewed banks' loan loss allowances to be understated by, on average, 25% (median: 8%). However, most of the AQR adjustments were not due to formal violations of accounting rules, but rather signaled a shift in supervisory reporting preferences within a common accounting framework, with the ECB generally preferring higher levels of provisioning than the national supervisors previously in charge of bank supervision.

This paper explores the effect of these changes in the reporting preferences of the responsible supervisor and the corresponding supervisory disclosures. In particular, we address three research questions. First, we examine whether banks adjust their reporting behavior following the change of their responsible supervisor and the public assessment of their asset quality. Second, we investigate whether the change in supervisory responsibility is also associated with the market perception of bank transparency as reflected in lower information asymmetry and greater market liquidity. Third, we compare how the changes in reporting behavior and perceived transparency relate to both the shift in supervisory authority and third-party market monitoring.

We exploit the data made available by the ECB as part of the AQR exercise to address these questions. These supervisory disclosures provide a relatively clean measure of firm-level

[16] In addition to the Asset Quality Review, this Comprehensive Assessment (CA) included a stress test.

differences in regulatory reporting preferences, and ultimately regulatory scrutiny, between the prior national supervisors and the ECB. This is important because, across the board, the ECB is not a stricter supervisor per se.[17] The availability of a firm-level measure of changes in regulatory scrutiny differentiates our paper from prior studies on the effect of supervisory characteristics on bank reporting. Observable differences across regulatory regimes used in the literature are likely not only driven by supervisory characteristics, but also by macroeconomic conditions, idiosyncratic portfolio choices, and reporting incentives (Costello, Granja, and Weber, 2020; Nicoletti, 2018). Even for intra-firm changes in supervisory institutions, differences in supervisory characteristics need not uniformly affect supervised institutions (Agarwal, Lucca, Seru, and Trebbi, 2014; Granja and Leuz, 2019). For example, small banks with a straightforward business model can be supervised equally well by regulators with and without extensive resources. Similarly, concerns about regulatory capture that result from reputational concerns or future employment opportunities plausibly differ in the cross-section of banks.

In the first step of our analyses, we employ a panel of yearly bank-level accounting data over the period from 2011 to 2017 (i.e., three years before and three years after the introduction of the SSM in the Eurozone). To examine banks' reporting behavior, we focus on changes in loan loss provisioning and the classification of non-performing loans. Our research design benefits from the national regulators remaining responsible for the supervision of non-SSM banks. We include all other European banks that overlap in size with the SSM treatment sample as a benchmark group

[17] For example, Nordea, the largest bank in Sweden (which is not part of the Eurozone), relocated its headquarters from Stockholm to Helsinki in late 2018 in a conscious effort to fall under SSM supervision instead of the Swedish Finansinspektionen (Financial Times, 2017).

to enable a difference-in-differences estimation that controls for general time trends and macro-level shocks.

Controlling for changes in the underlying risk of the loan portfolio, we find, if anything, a negative standalone effect of SSM supervision on the level of loan loss provisions and non-performing loans. For instance, the ratio of non-performing to total loans decreased by 1.2 percentage points for SSM banks after becoming subject to ECB supervision, which amounts to about 18% of the average non-performing loan ratio of all banks in our sample period. This is in contrast to the common notion that the ECB is a generally stricter supervisor than the prior national regulators (Fiordelisi, Ricci, and Lopes, 2017), and is consistent with our understanding that the impact of the SSM is not uniform across all affected banks, but depends on the firm- and country-specific divergences in supervisory policy. Consequently, when we take the magnitude of the AQR adjustments into account, we find that against the negative base effect, reporting conservatism significantly increases with larger adjustments. We interpret this as evidence that banks' reporting choices are influenced by supervisory preferences beyond simple compliance with given accounting standards.

In the second step, we estimate panel regressions of monthly bid-ask-spreads as a proxy for market liquidity and information asymmetry among market participants for the subsample of listed treatment and control firms. We find that the SSM adoption is associated with a decrease in the bid-ask spreads of participating banks by about 16%. However, when we interact the SSM participation with the magnitude of a bank's AQR adjustment, we observe that this association is limited to those banks with greater AQR adjustments. This finding supports the view that supervisory scrutiny can reduce information asymmetry and contribute to a higher level of perceived transparency.

In the third step, we examine the cross-sectional variation in the changes in reporting behavior and market liquidity around the SSM adoption more closely. In particular, to gauge the relative importance of enforcement and market discipline, we test to what extent the changes are attributable to supervisory reporting preferences (i.e., differences between the ECB and the national supervisor) or to the strength of market forces at the firm level. We find that the likelihood of political capture under local regulation and the increase in the quality of the regulatory infrastructure are associated with the change in banks' reporting behavior. Banks that are subject to the greatest shift in these supervisory characteristics exhibit the strongest increase in loan loss provisions and loans classified as non-performing. However, we fail to find evidence that an increase in regulatory scrutiny per se also translates into higher stock liquidity. Instead, rather than with regulatory characteristics, the changes in market liquidity around SSM adoption are associated with the strength of third-party market monitoring through, e.g., depositors and other providers of bank funding. The latter finding implies that even where supervisory action is not perfectly aligned with market demand for information, supervisory disclosures like the publication of the AQR results can stimulate market discipline and push banks to increase their level of transparency.

Our study contributes to different streams of the literature. First, it is related to research on the influence of supervisory institutions and their enforcement on reporting outcomes and firm transparency in general and, in particular, in the banking industry (Bischof, Daske, Elfers, and Hail, 2020; Costello et al., 2016; Granja, 2018; Granja and Leuz, 2019; Leuz and Wysocki, 2016; Nicoletti, 2018). We add to this literature by focusing on a clearly identified setting that is characterized by within-firm changes in the responsible supervisor and a firm-level measure of supervisory reporting preferences that captures variation in the potential impact of the reform. Our results on the institutional determinants of the SSM/AQR effect are also related to the literature on the consequences of intra-agency and interagency heterogeneity for regulatory outcomes (Busuioc, 2015; Fremeth and Holburn, 2012; Macher, Mayo, and Nickerson, 2011) and on political influence and regulatory capture (Agarwal, Amromin, Ben-David, and Dinc, 2018; Lambert, 2018).

Second, our paper adds to the literature on the effects of supervisory disclosure. In particular in the banking industry, disclosures about enforcement actions or regulatory stress tests have been found to be informative and to elicit market discipline by investors (Petrella and Resti, 2013; Morgan, Peristiani, and Savino, 2014; Flannery, Hirtle, and Kovner, 2017; Fernandes, Igan, and Pinheiro, 2017). These disclosures can also have feedback effects on the supervisor's choice of enforcement actions (Kleymenova and Tomy, 2020) and on firms' reporting behavior (Bischof and Daske, 2013; Duro et al., 2019). We complement these studies by investigating under which conditions supervisory disclosure can facilitate changes in banks' reporting behavior and perceived transparency.

Finally, our paper adds to the topical literature on the SSM. Prior research focuses either on the determinants (Acharya and Steffen, 2014; Homar, Kick, and Salleo, 2015; Steffen, 2014) or on the immediate market reaction to the publication of the results of the AQR and the contemporaneous stress test (Carboni, Fiordelisi, Ricci, and Lopes, 2017; Lazzari, Vena, and Venegoni, 2017; Sahin and de Haan, 2016). Regarding the real effects of the SSM adoption, Fiordelisi et al. (2017) document that affected banks reduced their credit supply in the run-up to the SSM launch to improve their equity capital ratios.[18] Our study contributes to this literature by

[18] Eber and Minoiu (2017) also find that banks subject to the Comprehensive Assessment adjusted their leverage, mainly by reducing lending and wholesale funding. Gropp, Mosk, Ongena, and Wix (2019) make a similar point regarding the 2011 stress test by the European Banking Authority (EBA).

providing evidence on how the SSM influenced the long-term transparency of supervised institutions.

The remainder of the paper proceeds as follows. In Section 2, provide more details on the SSM and the AQR disclosures and develop our empirical predictions. In Section 3, we outline the research design, describe the sample selection, and provide descriptive statistics. Section 4 presents the results of the baseline analysis of the SSM/AQR effects on banks' accounting behavior and perceived transparency, and the cross-sectional tests along the dimensions of changes in supervisory enforcement and the intensity of market monitoring. Section 5 concludes.

2.2. Institutional setting and empirical predictions

2.2.1. Bank supervision and accounting enforcement under the Single Supervisory Mechanism

To reinstate trust in the financial markets after the European sovereign debt crisis, policymakers and regulators called for a coordinated approach regarding the governance of financial system stability. A major aspect of these initiatives was the integrated supervision of cross-border banking activities, as banking supervision was predominantly performed by national supervisors even for large, internationally active banking groups.[19] To facilitate the harmonization

[19] National supervisors of cross-border banking groups were already engaging in information sharing in the form of "supervisory colleges" before the crisis. These supervisory colleges were formed to foster coordination between the different national supervisors and were formally mandated by the EU Capital Requirements Directive II (Directive 2009/111/EC). However, the degree of collaboration between national supervisors within the colleges varied significantly, often leading to inefficient microprudential supervision. For instance, during the chaotic bailout of the Fortis banking group, regulators from Belgium, Luxemburg, and the Netherlands had difficulties to align their actions (Financial Times, 2009).

of the European system of banking supervision, the Eurozone countries formally agreed to form a Banking Union in December 2012.

This Banking Union consists of three building blocks: the SSM, the Single Resolution Mechanism, and a common deposit insurance scheme. Under the SSM, the ECB formally assumed responsibility as the prudential supervisor of all banks in the Eurozone as of November 2014 (Regulation EU/1024/2013). At the same time, the ECB automatically redelegated the supervision of all "non-significant" institutions back to the originally responsible national supervisors.[20] The ECB determines the significance of a bank on a country-by-country basis depending on predetermined size cutoffs (total assets above EUR 30 billion or the bank being among the three largest financial institutions of a country) and the extent of its cross-border activities. As such, with the adoption of the SSM regulation, the ECB became the direct supervisor of 120 major financial institutions in 18 Eurozone countries (plus Lithuania, which adopted the Euro in 2015), aiming to *"build on the best supervisory practices that are already in place"* (ECB, 2014a). Prudential supervision for these significant institutions is carried out by joint supervisory teams composed of both supervisory staff directly employed by the ECB and representatives assigned from the national supervisors of countries where the bank has subsidiaries or significant branches. To impede regulatory capture, team members rotate on a regular basis (ECB, 2018b). Although the ECB sets the supervisory agenda and the joint supervisory teams are always headed by ECB

[20] The General Court of Justice eventually ruled that national authorities had no formal autonomous competence for prudential supervision of euro area financial institutions (Case T-122/15 Landeskreditbank Baden-Württemberg vs. ECB, 2017). However, once prudential supervision tasks were redelegated to a national supervisor, there was no formal accountability mechanism that would give the ECB any power to sanction the national supervisor besides the latent threat to reassume the role of the supervisor of a less significant institution in the respective country (Karagianni and Scholten, 2018).

staff, the teams rely extensively on the national supervisor's existing supervisory infrastructure as well as on their local staff in their operations (European Court of Auditors, 2016; IMF, 2018).

On October 26, 2014, shortly before the introduction of the SSM, the ECB and the European Banking Authority (EBA) released the results of a Comprehensive Assessment (CA) that consisted of the AQR and a stress test of major Eurozone banks.[21] While the stress test gauged the banks' resilience against macroeconomic shocks, the AQR involved a detailed review of bank balance sheets with the objective of harmonizing the measurement of banks' risk exposures and increasing the quality of public information. In particular, the AQR assessed the adequacy of loan loss provisions, collateral valuations, and the classification of loan exposures as non-performing. It was a supervisory exercise of unprecedented scale (ECB, 2014b), lasting 12 months, involving more than 6,000 staff, and costing nearly EUR 500 million for external auditors and consultants. In 2015 and 2016, the EBA carried out two more AQRs to prepare the inclusion of additional banks to the SSM supervisory system (2015: 13 banks, 2016: 3 banks). Importantly, the ECB did not intend the findings of the AQR to trigger immediate accounting restatements, and only 8% of the additionally required loan loss provisions were stated to stem from actual violations of binding accounting rules (ECB, 2014b). Instead, the AQR adjustments revealed differences in the regulatory reporting preferences between the ECB and individual national regulators that originate from the discretion inherent to the application of financial reporting standards for loan loss provisioning.

[21] While there was significant overlap between CA inclusion and participation in the SSM, some banks did not become subject to ECB supervision but were part of the AQR, and vice versa. Specifically, between 2014 and 2017, 136 banks were included in the SSM, but seven of these were never included in an AQR. In the AQRs, the ECB assessed 142 banks, but 13 of these AQR banks were never included in the SSM. Therefore, the overlap between SSM and AQR comprises a set of 129 banks (see Table 1 for details).

2.2.2. Banks' reporting behavior around the supervisory AQR disclosures

Formal supervisory enforcement and informal supervisory influence are an important determinant of firms' reporting behavior (Christensen, Hail, and Leuz, 2013; Gipper, Leuz, and Maffett, 2019; Holthausen, 2009). In the banking sector, bank supervisors tend to dominate the public enforcement of reporting regulation. They have economic resources and legal powers that usually outmatch those of general accounting supervisors (such as the securities market regulator) by a wide margin (Bischof et al., 2020). However, bank supervisors can have ambiguous preferences regarding bank transparency, which are not necessarily aligned with investors' demand for information. For example, supervisors prefer at least some specific banks to be opaque to facilitate the orderly resolution of troubled institutions, to avoid market concern, or to protect the supervisor's reputation (Gallemore, 2019; Steffen, 2014).

We expect that the transnational unification of supervisory institutions under the SSM affects bank reporting, beyond formal compliance with accounting standards, through a harmonization of these supervisory preferences. Importantly, this effect is not necessarily uniform at the individual firm level, but depends on the relative divergence in supervisory reporting preferences between the national regulator and the ECB, which becomes manifest in the bank-specific AQR adjustment. We therefore predict that SSM banks will adjust their accounting policies corresponding to the magnitude of these published accounting adjustments.

The extent to which the ECB will intervene and enforce its reporting preferences likely depends on a country's specific institutional setup, such as the sources of the national supervisor's prior leniency and the national supervisor's relative resources and bargaining power. Supervisory leniency can be caused by a lack of supervisory resources, which reduces the ability to detect shortcomings and to enforce corrective action (Fremeth and Holburn, 2012; Jackson and Roe, 2009; Macher et al., 2011). At the same time, the national supervisors' endowment and ability also likely determine their bargaining power in determining supervisory policies relative to the ECB, which initially had to rely substantially on local resources and the existing supervisory infrastructure (European Court of Auditors, 2016; IMF, 2018). Against this backdrop, we predict that the adjustment of banks' accounting behavior is more pronounced in countries with relatively weak national supervisors.

Another important potential cause of supervisory leniency is institutional capture (Lambert, 2018; Macher and Mayo, 2012; Stigler, 1971). As the ECB is a relatively independent institution regarding the influence of individual governments or national interest groups (Loipersberger, 2018), the SSM implementation likely mitigates such issues, and we expect that SSM banks are required to adjust their accounting policies more strongly in local environments that indicate prior capture of the national supervisor.

In addition to the direct intervention by the supervisor, we expect that the SSM implementation also affects banks' reporting behavior indirectly through market pressure that stems from the disclosure of the AQR results. Such supervisory disclosure provides market participants with private supervisory information and allows them to impose market discipline on the supervised firms, which in turn can induce changes in firm behavior (Duro et al., 2019). The more a bank's funding structure or the perceived threat of distress facilitate market monitoring, the greater we expect banks to adjust their reporting choices.

2.2.3. Bank transparency around the supervisory AQR disclosures

Where the AQR adjustments match market concerns about banks' portfolio risk (Carboni et al., 2017; Lazzari et al., 2017), their publication and the corresponding changes in reporting behavior can increase banks' perceived transparency and, through the reduction in adverse selection, induce an increase in stock liquidity (Diamond and Verrecchia, 1991; Leuz and Verrecchia, 2000; Verrecchia, 2001). In addition, even if the AQR adjustments are not fully aligned with investors' informational needs (e.g., because they are understood simply as an indicator of unconditional supervisory conservatism), they can suggest a higher level of supervisory strictness under the SSM that might affect the perception of banks' reporting quality in general. Similarly, supervisory disclosures that reveal substantial AQR adjustments likely trigger investor attention that extends to all aspects of financial reporting, which in turn can generate market pressure for banks to increase their overall level of public information.

2.3. Research design and data

In this section, we describe the empirical identification strategy and develop the regression models to test our main predictions regarding the effect of the SSM introduction and the supervisory AQR disclosures on bank's reporting behavior and, consequently, on market liquidity. We then discuss the sample selection and provide descriptive statistics on our sample of European banks.

2.3.1. Empirical model

We evaluate the changes in bank reporting and transparency around the SSM adoption and after the supervisory AQR disclosures from two perspectives. First, we analyze changes in banks' loan loss reporting behavior around the AQR disclosures using panel regressions with different key ratios from banks' yearly financial statements as the dependent variable. Second, we examine whether the observed changes in reporting behavior are associated with an increase in bank transparency and lower levels of information asymmetry (as reflected in bid-ask spreads). The analyses rely on publicly available data on the AQR adjustments. These adjustments provide us with a granular and firm-specific measure of the extent to which the newly adopted supra-national SSM supervision reflects a change in supervisory reporting preferences (compared to the previous supervision by the local authority).

In both sets of tests, we use a difference-in-differences design that exploits the size overlap between AQR participants and European non-SSM banks arising from the different size thresholds for AQR participation in the Eurozone countries (Gropp et al., 2019). We include only non-SSM banks that are at least as large as the smallest SSM bank in the benchmark sample to avoid that our results are driven by different business models or funding strategies that are potentially correlated with bank size. Our research design also benefits from the staggered introduction of the SSM from 2014 to 2016 (with the majority of banks being included in 2014). Together, these features allow us to control for general time trends and market-wide shocks in reporting behavior and stock liquidity.

To analyze banks' reporting behavior, we estimate variations of the following difference-in-difference regression model for a panel of yearly observations of the treatment and benchmark firms over the 2011 to 2017 period.

$$Loss\_Recognition = \beta_0 + \beta_1\, SSM\_Treated + \beta_2\, SSM\_Treated * AQR + \sum \beta_i\, Controls$$
$$+ \sum \beta_j\, Fixed\ Effects + \varepsilon \qquad (1)$$

We employ four accounting ratios that represent the loan loss reporting behavior of banks as dependent variable. Specifically, we use (1) the ratio of periodic loan loss provisions to total gross loans (*LLP Ratio*), (2) the ratio of the total loan loss allowance to total gross loans (*LLA Ratio*), (3) the ratio of loan loss allowances to non-performing loans (*Coverage Ratio*), and (4) the ratio of non-performing loans to total gross loans (*NPL Ratio*). There are two main variables of interest. First, the difference-in-difference estimator *SSM_Treated* is a binary indicator variable that takes on the value of '1' beginning in the first year that an SSM bank becomes subject to ECB supervision. Second, *SSM_Treated * AQR* captures the potentially heterogeneous treatment effect and is the interaction of *SSM_Treated* and the continuous variable *AQR*. We compute *AQR* as the magnitude of the ECB's disclosed adjustment of a bank's loan loss provisions (scaled by the concurrent loan loss allowance) as a result of the Asset Quality Review. *Controls* denotes the following lagged firm-level and macroeconomic control variables: *Size* as the natural logarithm of total assets, *RoA* as the ratio of pre-provisioning income to total assets as a measure of banks' profitability, *Tier 1* as the ratio of banks' tier 1 capital to risk-weighted assets, *Cost-to-Income* as the operating expense divided by operating income measuring banks' efficiency, *GDP* as the annual gross domestic product growth rate in the respective country obtained from the World Bank, and *RWA* as the ratio of risk-weighted assets to total assets as a measure of the underlying portfolio risk. We add changes in non-performing loans from year t–1 to year t in regressions of loan loss provisions to control for non-discretionary changes in delinquency rates. We include year- and firm-fixed effects, which account for the general time trend as well as time-invariant bank and country characteristics (e.g., the quality of the legal system or the development of capital markets). As such, our fixed-effects structure subsumes factors that are specific to a certain year (e.g., the sovereign debt crisis). In all our tests, we draw statistical inferences based on standard errors clustered by bank to adjust for time-series correlation (Petersen, 2009).

For the liquidity analysis, we estimate the SSM effect in a similar regression model using a panel of monthly observations of the subsample of listed sample banks from 2011 to 2017:

$$Log(Bid\text{-}Ask\text{-}Spread) = \beta_0 + \beta_1\, SSM\_Treated + \beta_2\, SSM\_Treated * AQR + \sum \beta_i\, Controls$$

$$+ \sum \beta_j\, Fixed\ Effects + \varepsilon \qquad (2)$$

where the dependent variable *Bid-Ask Spread* is the monthly median quoted spread between the bid and ask price, and *SSM_Treated* is a binary indicator variable that now takes on the value of '1' for treatment banks beginning in the first month after becoming subject to ECB supervision. *SSM_Treated * AQR* is the interaction between *SSM_Treated* and the magnitude of the ECB's disclosed adjustments of a bank's loan loss provisions, scaled by the concurrent loan loss allowance. *Controls* is a vector of firm-specific controls that capture additional determinants of stock liquidity: the absolute value of the monthly *Abnormal Stock Return* (based on a simple market model), *Market Value*, the monthly median of daily *Share Turnover*, and *Return Variability* measured by the standard deviation of daily stock returns. We estimate the liquidity regressions in a log-linear form with the natural logarithm of the dependent and control variables, and lag the control variables by 12 months. We include country-month and firm-fixed effects to control for country-specific time trends as well as for time-invariant bank and country characteristics.

2.3.2. *Sample selection and descriptive statistics*

Our sample period begins in 2011, three years before the launch of the SSM, and runs until 2017, three years after.[22] We collect annual bank accounting information from S&P Global Market Intelligence (formerly SNL Financial) and capital market data from Thomson Reuters Datastream. Table 2.1 summarizes the sample selection process. For the accounting analysis, the initial treatment sample includes all 136 SSM banks, of which we keep 129 banks that were also subject to an AQR in 2014, 2015, or 2016. We exclude 12 banks that were nationalized during the sample period, and drop six more banks due to missing data on dependent or independent variables. The final treatment sample comprises 111 SSM/AQR banks with 667 annual observations.

For the control group, we begin with all 4,600 EU banks from the S&P universe that were not included in the SSM. We exclude 755 banks that were either directly owned by a treatment bank or shared their direct or ultimate parent with a treatment bank.[23] We additionally exclude 748 banks due to missing data. Because the AQR focused on banks with significant lending activity, we follow Fiordelisi et al. (2017) and exclude 233 control banks that are in the bottom fifth percentile of loans to total assets.

[22] From 2018, Eurozone banks that apply IFRS started to report loan loss provisions under IFRS 9's new expected credit loss model, which impairs the comparability of post-2018 accounting numbers with earlier periods (when banks applied the incurred loss model under IAS 39). This supports our choice of the sample period.

[23] Ownership information in S&P Global Market Intelligence is static and only available for the latest respective update. We additionally use ownership information from the 2012 Bureau van Dijk Bankscope tape to complement the ownership test with earlier periods.

Table 2.1 Sample selection

Panel A: Overview of AQR/SSM banks

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Year	*AQR*	*New SSM Banks*	*SSM Dropouts*	*SSM Banks*	*Overlap (1) & (2)*
2014	130	120	-	120	119*
2015	9	15	6	129	9**
2016	3	1	4	126	1
2017	0	0	1	125	0
Treatment Sample					**129**

Panel B: Sample selection procedure

	Treated Banks	*Treated Obs.*	*Control Banks*	*Control Obs.*
All SSM banks	136			
Less: banks not in AQR	(7)			
AQR & SSM banks	**129**	**903**		
Less: AQR Banks nationalized during sample period	(12)	(84)		
AQR & SSM Banks	117	819		
All other banks in Europe with data from S&P			4,600	32,200
Less: Owned by a treatment bank			(755)	(5,285)
Less: Missing data on dependent or control variables	(6)	(152)	(748)	(11,448)
Less: Bottom 5% TL/TA			(233)	(1,086)
Less: TA < smallest treatment bank			(1,297)	(6,627)
Total Sample (accounting analysis)	**111**	**667**	**1,567**	**7,754**

Table 2.1 Panel A shows the number of banks that participated in an AQR or became subject to the SSM. Column (1) indicates the number of participants in the point-in-time AQR in a given year, column (2) shows how many new banks became subject to ECB supervision under the SSM, column (3) indicates how many banks previously in the SSM dropped out of the SSM again, column (4) presents the total number of banks in the SSM in a given year, and column (5) shows how many banks became subject to ECB supervision under the SSM and also participated in an AQR during the sample period.*Out of these 119 banks 5 participated in the CA in 2015 but joined the SSM in 2014. **Out of these 9 banks, 5 were assessed in 2014 but joined the SSM in 2015, 1 bank was assessed in 2016 but joined the SSM in 2015. Panel B illustrates the sample selection procedure for the treatment and the control group. The sample period includes all years over the 2011-2017 period using all European banks as control that are at least as large as the smallest SSM/AQR bank. We exclude banks that are owned by a treatment bank or that are in the bottom 5th percentile of the total loans to total assets ratio, and bank observations that have missing data on any control variable or all dependent variables.

The ECB determines on a country-by-country basis which banks are classified as "significant" and therefore become subject to ECB supervision. This selection is mainly determined by bank size (banks which exceed total assets of EUR 30 billion or are among the three largest financial institutions of a country).[24] As such, SSM/AQR banks are on average larger than non-treatment banks. However, they significantly overlap with the control banks due to the country-specific application of the selection criteria. Following Gropp et al. (2019), we exploit this size overlap to construct the control group as an "overlap sample" of banks that are at least as large as the smallest SSM bank in the treatment sample. This procedure alleviates concerns that we capture inherent differences in business models or funding strategies that stem from the size difference between our treatment and control group.[25] After excluding banks that do not overlap with the size range of SSM banks, the final control group comprises 1,567 banks and 7,754 annual observations. We use the subsample of banks with publicly listed equity and trading data available on Datastream for the liquidity analysis. Using the same selection criteria as for the accounting analysis yields a final sample of 6,141 monthly observations for AQR/SSM banks and the control group.

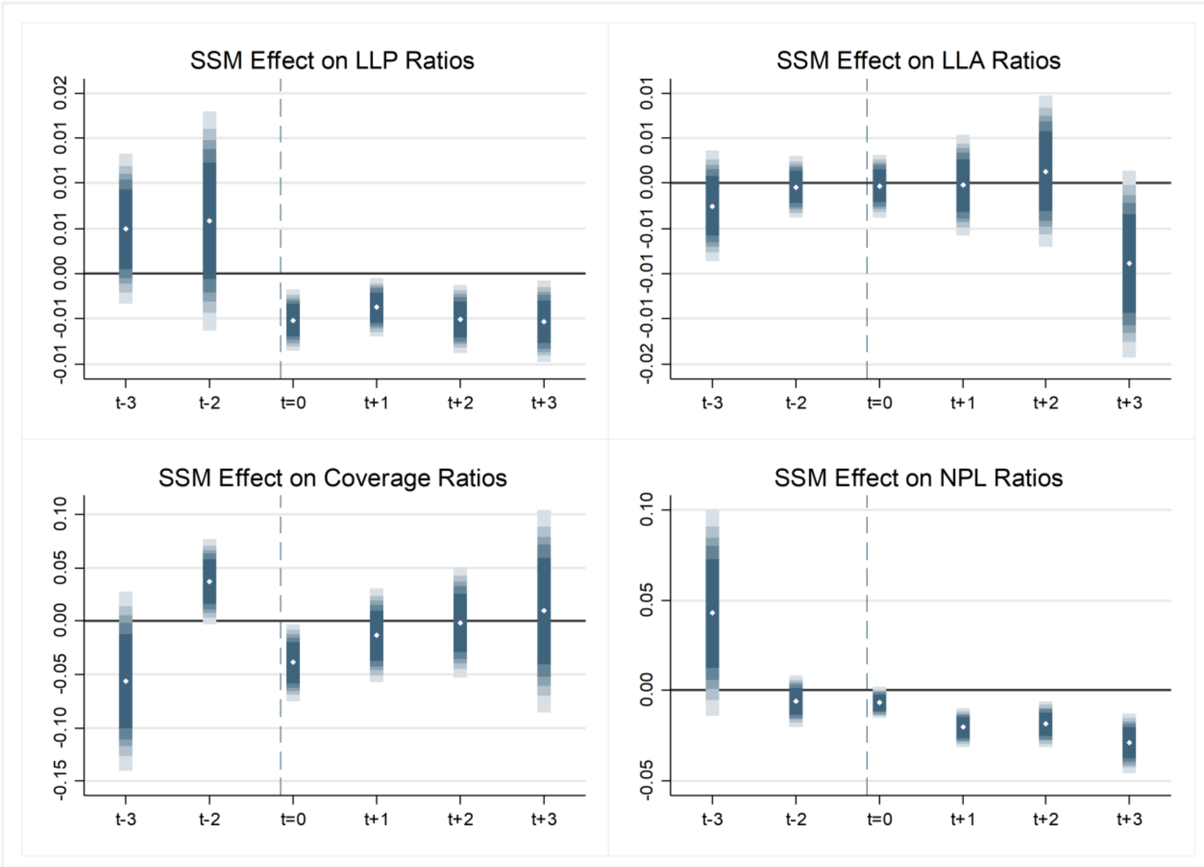
To establish the validity of assuming a parallel trend among our treatment and control group, Figure 2.1 reports the coefficient estimates for an interaction of the SSM treatment indicator with dummy variables for each year in the different specifications of Eq. (1), using t-1 (the year

[24] Additional selection criteria are a) the economic importance of the bank for the country or the EU economy as a whole, b) the significance of cross-border activities, and c) whether the bank receives direct public financial assistance.

[25] We validate our results using entropy balancing as a quasi-matching technique that alleviates concerns about potential differences between our treatment and control sample (Hainmueller, 2012) and that is widely used in recent finance and accounting research (Chapman, Miller and White, 2019; Ferri, Zheng and Zhou, 2018; Shroff, Verdi and Yost, 2017). Under entropy balancing, the observations in our sample are reweighted so that the distribution of the control variables in the control group is as similar as possible to the distribution in the treatment group along the first three moments (mean, variance, and skewness). The findings from this analysis are qualitatively and quantitatively similar to the ones presented in the results section (see Appendix C).

before a bank becomes subject to SSM supervision) as a benchmark. These coefficients are never significantly different from zero (at a 5% significance level) in the pre-SSM period, mitigating concerns about systematically different time-trends or anticipation effects that might bias our difference-in-difference results.

Figure 2.1 Accounting effects around SSM introduction and AQR disclosures



The figure shows the reporting patterns around the SSM adoption and the AQR disclosures. We estimate the model in Eq. (1) but replace the *SSM Treated* coefficient with seven separate indicator variables, each marking the year relative to the first treatment year over the 2011 to 2017 period. We omit the indicator for year t-1, which serves as benchmark for all other years. The figure plots the coefficient estimates for the seven years (except t-1) together with their confidence intervals for loan loss provisions, loan loss allowances, coverage ratios, and non-performing loans. We include all control variables and fixed effects from Eq. (1) in the estimation. Standard errors are clustered by bank.

Panel A of Table 2.2 presents descriptive statistics for all firm-level variables used in the accounting and liquidity regression analyses. The four dependent variables of interest in the accounting analysis show considerable variation in our sample. Banks recognize annual loan loss provisions of 0.5% of total gross loans on average (ranging up to 5.6% at the 99th percentile), and the loan loss allowance covers 3.3% (1.8%) of banks' total loans at the mean (median). The average adjustment to loan loss provisions disclosed through the AQR amounts to 25.9% of the loan loss allowance for SSM/AQR treatment banks. Panel B of Table 2.2 breaks down the sample composition by country and provides detailed information on the country-level variables. A large proportion of the sample banks is located in Germany and Italy, which corresponds to the distribution of the bank population in Europe.

Table 2.2 Descriptive statistics

Panel A: Descriptive statistics for firm-level variables

	Bank-years	*Mean*	*Std. Dev.*	*P1*	*P25*	*Median*	*P75*	*P99*
Accounting Analysis								
Tier 1	8421	0.149	0.066	0.066	0.112	0.135	0.165	0.505
Size	8421	14.821	1.506	13.094	13.718	14.405	15.461	19.754
Cost-to-Income	8421	0.658	0.158	0.232	0.585	0.665	0.735	1.230
RoA	8421	0.006	0.008	-0.017	0.002	0.005	0.009	0.037
Risk-weighted Assets	8421	0.560	0.165	0.125	0.466	0.569	0.657	0.961
GDP	8421	0.014	0.017	-0.028	0.005	0.017	0.021	0.052
ΔNPL	0.002	0.020	-0.054	-0.006	-0.001	0.004	0.097	0.002
Loan loss provision (LLP) Ratio	8385	0.005	0.012	-0.026	0.000	0.002	0.008	0.056
Loan loss allowance (LLA) Ratio	8392	0.033	0.040	0.000	0.008	0.018	0.042	0.209
Non-performing loans (NPL) Ratio	6180	0.066	0.076	0.000	0.018	0.035	0.082	0.365
Coverage Ratio (LLA/NPL)	6163	0.562	0.409	0.138	0.384	0.492	0.620	3.217
AQR	667	0.259	0.927	0.000	0.021	0.084	0.221	5.606
Firm-Level Partitioning Variables								
Junk Rating	2444	0.065	0.247	0.000	0.000	0.000	0.000	1.000
Short-term Funding	1479	0.226	0.224	0.000	0.045	0.139	0.368	0.809
Funding Cost Volatility	8026	0.003	0.002	0.000	0.002	0.002	0.003	0.011
Liquidity Analysis	*Bank-months*							
Bid-Ask Spread	6141	0.010	0.015	0.000	0.001	0.004	0.013	0.089
Abs(Abnormal Stock Return)	6141	0.065	0.071	0.001	0.019	0.043	0.084	0.431
Market Value (EUR million)	6141	7634.528	13862.092	23.200	336.539	1638.144	7264.929	70025.555
Share Turnover	6141	0.250	1.660	0.000	0.000	0.001	0.004	15.175
Return Variability	6141	0.023	0.015	0.002	0.014	0.019	0.028	0.089

(continued)

Table 2.2 (cont.)

Panel B: Sample composition and country-level partitioning variables

					Country-Level Partitioning Variables						
Country	*Control Banks (Bank-years)*		*Treatment Banks (Bank-years)*		*Distrust EU*	*Distrust ECB*	*Anti-EU Party*	*Recession*	*Reg. Quality*	*Equity Ownership*	*Listed Firms*
Austria	45	(201)	7	(40)	0.49	0.41	1	0.018	1.488	–	0.186
Belgium	4	(13)	59	(29)	0.49	0.46	0	0.011	1.158	0.160	0.213
Bulgaria	12	(67)	–	–	0.34	0.30	0	0.010	0.568	–	6.706
Croatia	6	30	–	–	0.51	0.45	0	-0.012	0.395	–	3.346
Cyprus	6	(27)	3	(17)	0.68	0.64	0	-0.012	1.099	–	4.023
Czech Republic	7	(40)	–	–	0.48	0.41	0	0.005	1.006	0.020	0.063
Denmark	42	(250)	–	–	0.40	0.24	0	0.008	1.687	0.140	0.504
Estonia	2	(8)	2	(14)	0.18	0.20	0	0.060	1.677	0.040	0.526
Finland	18	(100)	4	(26)	0.34	0.25	1	0.005	1.884	0.310	0.492
France	20	(82)	11	(71)	0.52	0.48	0	0.012	1.079	0.180	0.174
Germany	845	(4160)	19	(118)	0.53	0.53	1	0.018	1.703	0.120	0.153
Greece	6	(18)	4	(27)	0.76	0.75	1	-0.082	0.329	0.100	1.013
Hungary	7	(35)	–	–	0.43	0.42	0	0.000	0.752	0.060	0.343
Ireland	7	(33)	3	(19)	0.47	0.52	1	0.015	1.765	–	0.166
Italy	257	(1303)	14	(88)	0.54	0.50	1	-0.012	0.642	0.070	0.135
Latvia	6	(18)	3	(9)	0.36	0.32	0	0.053	1.172	0.000	1.787
Lithuania	5	(16)	3	(9)	0.25	0.24	1	0.051	1.194	0.110	0.928
Luxembourg	11	(56)	4	(23)	0.38	0.31	1	0.011	1.631	0.060	0.378
Malta	3	(17)	4	(23)	0.29	0.15	0	0.020	1.083	0.230	2.127
Netherlands	23	(116)	4	(26)	0.45	0.29	1	0.004	1.769	–	0.110
Poland	18	(75)	–	–	0.29	0.25	0	0.033	1.055	0.110	1.599
Portugal	12	(44)	3	(20)	0.51	0.51	1	-0.028	0.750	0.120	0.205
Romania	11	(55)	–	–	0.31	0.28	0	0.017	0.581	–	0.406
Slovakia	7	(40)	3	(21)	0.42	0.37	1	0.022	0.890	0.000	0.664
Slovenia	10	(46)	4	(27)	0.49	0.51	1	-0.010	0.662	0.210	1.022
Spain	44	(189)	11	(60)	0.61	0.68	0	-0.020	0.750	0.150	2.483
Sweden	48	(273)	–	–	0.40	0.30	0	0.011	1.811	0.250	0.484
United Kingdom	85	(442)	–	–	0.61	0.44	0	0.015	1.826	0.110	0.612
Total	**1,567**	**(7,754)**	**111**	**(667)**							

Table 2.2 Panel A shows descriptive statistics for all firm-level variables used in our accounting and liquidity tests. Panel B shows the distribution of banks, bank-years, and raw values of the country-level partitioning variables across countries. All variables are defined in Appendix B.

2.4. Empirical results

In this section, we first describe the baseline results of the analysis of banks' reporting behavior around the SSM introduction and the corresponding AQR disclosures. Next, we examine the potential effect on banks' stock liquidity as an indicator of perceived firm transparency. We conclude with an analysis of cross-sectional differences in the changes in reporting behavior and stock liquidity.

2.4.1. Changes in financial reporting following SSM adoption

We begin by estimating the effect of the SSM implementation and contemporaneous disclosure of the AQR results on different credit risk-related reporting outcomes and report our baseline results in Table 2.3.[26] Columns (1) and (2) reveal that the adoption of the SSM is negatively associated with the level of loan loss provisions of participating banks. On average, loan loss provisions (scaled by total gross loans) decrease by 0.5 percentage points (p-value < 0.1%) upon SSM adoption relative to non-SSM banks, which is both statistically significant and economically meaningful. However, in line with our predictions, the supervisory shift does not uniformly affect all banks to a similar extent. Column (2) highlights that a bank with an average AQR adjustment disclosure of 25.9% decreases its loss provisions by 0.078 percentage points (0.003 x 0.259; p-value < 1%) less than a bank with no adjustment. This translates to an average marginal increase of the loan loss provision ratio for treatment banks of 9.3%, which is economically meaningful. Columns (3) and (4) report the results for banks' loan loss allowances. While the average effect of the SSM adoption is also negative (-0.2 percentage points, p-value=0.538), but statistically insignificant, we observe a marginal increase by 0.259 percentage

[26] The results are qualitatively and quantitatively similar if we exclude 2014 as the initial treatment year, suggesting that we indeed measure a long-term shift in reporting behavior.

points (p-value < 5%) in the loan loss allowance for treatment banks with an average AQR adjustment. We draw similar inferences for the coverage ratio (the ratio of the loan loss allowance to non-performing loans) in columns (5) and (6). Banks with an average AQR adjustment report more conservatively and increase their coverage ratios by 1.06 percentage points (p-value < 1%) relative to banks with no adjustment. In columns (7) and (8), the ratio of non-performing loans (NPL) to total gross loans serves as dependent variable. Treatment banks, on average, decrease their non-performing loan ratios by 1.6 percentage points (p-value < 1%) upon introduction of the SSM. However, similar to the results on loan loss provisioning, we find that those banks with higher AQR adjustments classify on average 0.41 percentage points (p-value < 1%) more loans as non-performing, suggesting that they adopted stricter guidelines in appraising their portfolio quality.

Taken together, our findings reveal a substantial change in reporting behavior after the SSM implementation and the publication of the AQR results. Banks facing a greater adjustment of their loan loss provisions increase their level of loan loss provisions, loan loss allowances, and loans classified as non-performing subsequently relative to other treatment banks. We interpret this evidence as consistent with the notion that the increase in supervisory scrutiny for certain SSM banks, together with the disclosure of the corresponding AQR results, changed how banks report about their portfolio quality.

Table 2.3 Loan loss reporting following SSM introduction and AQR disclosures

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Dependent Variable:	*LLP Ratio*	*LLP Ratio*	*LLA Ratio*	*LLA Ratio*	*Coverage Ratio*	*Coverage Ratio*	*NPL Ratio*	*NPL Ratio*
Test Variables:								
SSM Treated	-0.005**	-0.005***	0.000	-0.002	-0.017	-0.027	-0.012**	-0.016***
	(0.012)	(0.005)	(0.968)	(0.538)	(0.457)	(0.264)	(0.033)	(0.006)
SSM Treated*AQR	–	0.003***	–	0.010**	–	0.041***	–	0.016***
		(0.000)		(0.022)		(0.001)		(0.000)
Control Variables:								
ΔNPL	0.077***	0.078***	–	–	–	–	–	–
	(0.000)	(0.000)						
Tier 1	0.027***	0.028***	-0.121***	-0.120***	-0.542*	-0.541*	-0.254***	-0.252***
	(0.002)	(0.001)	(0.000)	(0.000)	(0.081)	(0.082)	(0.000)	(0.000)
Size	0.004***	0.004***	-0.012***	-0.012***	-0.082	-0.083	-0.013**	-0.014**
	(0.003)	(0.004)	(0.000)	(0.000)	(0.189)	(0.182)	(0.041)	(0.029)
Cost-to-Income	-0.011***	-0.012***	-0.009**	-0.009**	-0.081	-0.083	-0.025***	-0.026***
	(0.000)	(0.000)	(0.031)	(0.021)	(0.288)	(0.277)	(0.001)	(0.000)
RoA	-0.059	-0.062	0.564***	0.557***	-0.624	-0.645	0.959***	0.942***
	(0.145)	(0.122)	(0.000)	(0.000)	(0.585)	(0.573)	(0.000)	(0.000)
GDP	-0.052**	-0.049**	0.250***	0.254***	0.412	0.452	0.607***	0.619***
	(0.014)	(0.019)	(0.000)	(0.000)	(0.425)	(0.383)	(0.000)	(0.000)
Risk-weighted Assets	0.005*	0.005*	-0.066***	-0.067***	-0.388***	-0.391***	-0.096***	-0.098***
	(0.066)	(0.079)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm
N	5,783	5,783	8,300	8,300	6,069	6,069	6,097	6,097
Adj. R^2	0.569	0.569	0.828	0.828	0.709	0.709	0.911	0.911

Table 2.3 shows regression results for the effect of SSM supervision, depending on the magnitude of the AQR impact, on the level of banks' loan loss provision ratio, loan loss allowance ratio, non-performing loan ratio, and coverage ratio. The sample comprises 1,678 treatment and control banks. *SSM Treated* is a binary indicator variable that takes the value of '1' beginning in the first year that a treatment bank is under SSM supervision. *AQR* is the impact of the AQR adjustment on loan loss provisions (i.e., additionally required loan loss provisions) scaled by the amount of the loan loss allowance in the year preceding the AQR. All other variables are defined in Appendix B. All bank-level control variables are lagged by one year. We include year and firm fixed effects in the regressions, but do not report the coefficients. We winsorize all variables at the 1% and at the 99% level. The table reports OLS coefficient estimates and (in parentheses) *p-values* based on robust standard errors clustered by bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

2.4.2. Changes in liquidity following SSM adoption

We next examine whether SSM supervision and the disclosure of the AQR results are associated with a higher level of perceived transparency as reflected in higher market liquidity for the subsample of publicly listed banks.

In column (1) of Table 2.4, we document a significant increase in liquidity for banks that fall under SSM supervision. However, column (2) reveals that the liquidity benefits are entirely attributable to the magnitude of the AQR adjustments. That is, the base coefficient estimate for the SSM introduction becomes statistically insignificant once we include an interaction term that captures variation in the impact of the new supervisory regime and, correspondingly, the supervisory AQR disclosures. For the average treatment bank in our sample (in terms of the magnitude of the AQR adjustment), bid-ask-spreads decrease by about 15% relative to the control group after the SSM implementation, which is economically meaningful, but not too large to be implausible.

Taken together, our findings suggest that those SSM banks that, relative to their prior national supervisors, experienced a substantial switch in supervisory reporting preferences became more forthcoming in recognizing problem loans, with market participants perceiving these banks to be more transparent.

Table 2.4 Liquidity effects following SSM introduction and AQR disclosures

Log(Bid-Ask Spread) as Dependent Variable	*(1)*	*(2)*
Test Variables:		
SSM Treated	-0.185*	-0.037
	(0.054)	(0.741)
SSM Treated*AQR	–	-0.865**
		(0.037)
Control Variables:		
Log(Market Value$_{t-12}$)	-0.117**	-0.111*
	(0.038)	(0.052)
Log(Share Turnover$_{t-12}$)	-0.057**	-0.062***
	(0.015)	(0.009)
Log(Return Variability$_{t-12}$)	0.025	0.032
	(0.568)	(0.459)
Abs(Abnormal Stock Return$_t$)	0.250	0.253
	(0.115)	(0.113)
Fixed Effects	Firm, Country*Month	Firm, Country*Month
N	5,565	5,565
Adj. R^2	0.922	0.922

Table 2.4 presents regression results for the effect of SSM supervision, depending on the magnitude of the AQR impact, on banks' stock liquidity. The sample comprises 104 treatment and control banks with publicly listed equity. The sample period is from 2011 to 2017. We use the natural logarithm of a firm's monthly median quoted daily *Bid-Ask-Spread* as the dependent variable. *SSM Treated* is a binary indicator variable that takes on the value of '1' beginning in the first month that a treatment bank is under SSM supervision. *AQR* is the impact of the AQR adjustment on loan loss provisions (i.e., additionally required loan loss provisions) scaled by the amount of the loan loss allowance in the year preceding the AQR. All other variables are defined in Appendix B. In the regression analyses, we use the natural logarithm of *Market Value*, *Share Turnover*, and *Return Variability*, and lag all control variables by 12 months. We include country-month and firm fixed effects in the regressions, but do not report the coefficients. The table reports OLS coefficient estimates and (in parentheses) p-values based on robust standard errors clustered by bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

2.4.3. Cross-sectional heterogeneity: enforcement and market monitoring

We proceed with a closer examination of the channels that drive changes in banks' reporting behavior. First, we study the role of stricter enforcement under SSM supervision and exploit cross-country variation in the institutional setup and in the likelihood of political capture of prior national supervisors before the SSM adoption. Second, we explore the role of market monitoring in response to the newly available disclosures and exploit firm-level variation in the potential strength of market discipline. For these cross-sectional analyses, we add an interaction term to Eq. (1) and (2) and estimate variations of the following difference-in-difference regression model:

$$\textit{Loss\_Recognition / Log(Bid-Ask-Spread)} = \beta_0 + \beta_1\ \textit{SSM\_Treated} + \beta_2\ \textit{SSM\_Treated * Split} + \beta_3\ \textit{SSM\_Treated * AQR} + \beta_4\ \textit{SSM\_Treated * AQR * Split} + \sum \beta_i\ \textit{Controls}_i + \sum \beta_j\ \textit{Fixed Effects}_j + \varepsilon \qquad (3)$$

Split stands for a vector of binary partitioning variables that allow us to capture systematic variation in the impact of SSM supervision and the AQR disclosures among our treatment banks. The main effect of *Split* is subsumed by the firm-fixed effects, and the control variables are the same as defined before.

We report the results of the cross-sectional tests in Table 2.5. In each Panel, columns (1) to (5) provide the results from OLS regressions using country-level splits that are supposed to capture institutional features that reflect changes in enforcement strength. In column (1), *Regulatory Quality* is a summary measure from the World Bank's Worldwide Governance Indicators (WGI) to proxy for the overall quality and strength of national supervisors (Kaufmann, Kraay, and Mastruzzi, 2010). We use a binary indicator that takes the value of '1' for countries with above median regulatory quality in 2014. We expect banks with high-quality national supervisors to react less to SSM supervision because prior leniency is more likely to be driven by intentional supervisory policy (instead of, e.g., lack of resources or incompetence). At the same time, high-quality regulators have more bargaining power to assert their supervisory approach against the ECB, which initially had to rely substantially on the national supervisors' resources (European Court of Auditors, 2016; IMF 2018). In column (2), *Recession* is a binary indicator for countries that experienced negative GDP growth during the two years before the SSM introduction. We assume that politicians prefer more lenient supervision during economic downturns to foster bank lending, which potentially conflicts with the aim of the banking regulator to promote a sound banking system. The ECB as a supranational institution is likely to be politically independent and therefore more able to enforce its more conservative reporting preferences against opposing political interest (Loipersberger, 2018). This is also the underlying rationale for the following variables that directly capture countries' political characteristics. We derive the *Distrust EU* split in column (3) and the *Distrust ECB* split in column (4) from the answers to the 2014 Eurobarometer survey in each sample country. *Distrust EU* describes the answers to the question "Do you trust the EU?"; *Distrust ECB* describes the answers to the question "Do you trust the ECB?". Both variables are binary indicator variables that take the value of '1' if a country's percentage of "No" answers (indicating distrust) is above the sample median. We expect that national supervisors experience political pressure towards a more lenient supervisory approach in countries where the population exhibits a pronounced distrust towards the EU or ECB. In the same spirit, *Anti-EU Party* in column (5) indicates whether a nationalist or euro-skeptic party had a significant influence in the national parliament in the respective country as of 2014. We gather information on national election results from the Manifesto Project (Volkens et al., 2019) and manually collect data on missing countries. We define a party to be significant if it received 5% or more votes in the national elections or was part of the government in 2014.

In columns (6) to (10), we present test statistics from the OLS regressions using firm-level splits that are supposed to capture the strength of market monitoring and, thus, the potential role of market discipline in shaping banks' reporting behavior and transparency. In column (6), *Junk Rating* is an indicator for banks with an S&P rating below BBB-. We expect that banks with a speculative grade rating are subject to increased attention from their equity and debt investors (Freixas and Laux, 2011; Schweitzer, Szewczyk, and Varma, 1992). In column (7), *Short-term Funding* is the ratio of deposits maturing in less than three months to total liabilities. We consider banks with more short-term funding to be more exposed to debt investor scrutiny (Berger and Turk-Ariss, 2015; Calomiris and Kahn, 1991; Flannery, 1994; Peria and Schmukler, 2001). Similarly, *Funding Cost Volatility* in column (8) is the pre-treatment standard deviation of interest expenses to total liabilities. If debt investors learn about banks risk exposure, banks mitigate expected funding drains by offering higher interest rates to risk-sensitive investors (Demirgüç-Kunt and Huizinga, 2010; Maechler and McDill, 2006; Peria and Schmukler, 2001). That is, we expect that banks with more risk-sensitive investors are subject to higher market monitoring and experience higher fluctuations in their funding costs. For these three firm-level measures, we use data from 2013, the year before the SSM introduction, to avoid potential feedback effects or problems of reverse causality.

We use two additional country-level indicators of general stock market development. In column (9), *Listed Firms* is the ratio of the number of domestic listed firms to GDP (in billions) in 2014 from the World Bank (LaPorta, Lopez-de-Silanes, and Shleifer, 2006). In column (10), *Equity Ownership* is the proportion of total household liquid assets directly invested in the stock market during 2008-2010 from Christensen, Maffett, and Vollon (2019). For both splits, we expect that a higher demand for information in more sophisticated capital markets, and therefore a stronger reaction to the AQR disclosures.

Panels A to D of Table 2.5 report the results from estimating Eq. (3) separately for each of the four dependent variables related to reporting behavior from Eq. (1). The tables allow the following insights: We observe a significantly negative coefficient on the triple interaction of *SSM_Treated * AQR * Regulatory Quality* for all dependent variables. We interpret this result as consistent with the idea that an efficient national regulator can maintain its prior preferences against the ECB, which initially had to rely on local resources to enforce its policy. We further find that the main coefficient of interest on the triple interaction of *SSM_Treated * AQR * Split* is generally positive and significant when we employ *Recession*, *Distrust EU*, and *Distrust ECB* (and, less consistently, *Anti-EU Party*) as indicators of potential political capture of the national supervisor. The incremental effect on reporting conservatism is substantive and can be up to an order of magnitude larger than the baseline effect of *SSM_Treated * AQR*. In line with our expectations, these findings indicate that the impact of a change in supervisory reporting preferences on firms' reporting behavior is particularly pronounced when it coincides with a material change in the supervisor's institutional and political setup, pointing at the role of institutional characteristics and supervisory enforcement for the outcome of a given supervisory policy.

However, we do not find conclusive evidence on the role of market monitoring in promoting changes in SSM banks' accounting policies. In Panels A to D of Table 2.5, the coefficients on the triple interaction of *SSM_Treated * AQR * Split* for the different partitioning variables in columns (6) to (10) are mostly insignificant, except for *Junk Rating*. These results suggest that the supervisory disclosure of the AQR adjustments did not spark market demand for corresponding accounting changes, implying that such adjustments were not in line with investors' informational needs after the initial AQR disclosure.

We present the results of our analysis of cross-sectional variation in the effect on market liquidity in Panel E of Table 2.5. In contrast to our findings on changes in accounting behavior, four of the five partitioning variables reflecting heterogeneity in the potential impact of the SSM introduction on supervisory enforcement in columns (1) to (5) are statistically insignificant. However, we find a consistent and economically substantial incremental effect in settings that suggest a high level of market monitoring and investor scrutiny. We interpret these results to be consistent with the idea that while regulatory enforcement is effective in implementing given supervisory reporting preferences, firm transparency is ultimately determined by idiosyncratic reporting incentives and, in particular, market demand. Our findings suggest that the supervisory disclosure of the AQR results was effective in generating market attention that gave rise to an overall higher level of bank transparency beyond an adjustment to the supervisory policy. Together, these results point at the important complementary role of traditional enforcement and supervisory disclosures in effectuating firm transparency.

Table 2.51 Cross-sectional variation in accounting and liquidity effects

Panel A: LLP ratio

	Institutional Setup					*Market Monitoring*				
LLP Ratio as Dependent Variable	*(1) Regulatory Quality*	*(2) Recession*	*(3) Distrust EU*	*(4) Distrust ECB*	*(5) Anti-EU Party*	*(6) Junk Rating*	*(7) Short-term Funding*	*(8) Funding Cost Volatility*	*(9) Listed Firms*	*(10) Equity Ownership*
Test Variables:										
SSM Treated	-0.013**	-0.002**	-0.004***	-0.003**	-0.005*	-0.004***	-0.000	-0.005***	-0.002	-0.002
	(0.017)	(0.040)	(0.007)	(0.042)	(0.055)	(0.006)	(0.964)	(0.001)	(0.175)	(0.124)
SSM Treated*AQR	0.038*	0.002***	0.002***	0.002***	0.002***	0.008	0.019*	0.005	0.004	0.012*
	(0.066)	(0.000)	(0.000)	(0.000)	(0.000)	(0.244)	(0.057)	(0.503)	(0.339)	(0.070)
SSM Treated*Split	0.011*	-0.010*	-0.003	-0.006*	-0.002	0.002	-0.006	-0.004	-0.006*	-0.009*
	(0.057)	(0.059)	(0.326)	(0.093)	(0.604)	(0.625)	(0.150)	(0.490)	(0.084)	(0.088)
SSM Treated*AQR*Split	-0.036*	0.023*	0.017*	0.025*	0.016	0.018	0.008	0.020	-0.001	-0.009
	(0.080)	(0.084)	(0.099)	(0.060)	(0.130)	(0.256)	(0.636)	(0.212)	(0.844)	(0.183)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm
N	5,783	5,783	5,783	5,783	5,783	1,825	1,308	4,157	5,437	5,267
Adj. R^2	0.571	0.571	0.570	0.570	0.570	0.357	0.588	0.575	0.575	0.556

(continued)

Table 2.5 (continued)
Panel B: LLA ratio

	Institutional Setup					*Market Monitoring*				
LLA Ratio as Dependent Variable	*(1) Regulatory Quality*	*(2) Recession*	*(3) Distrust EU*	*(4) Distrust ECB*	*(5) Anti-EU Party*	*(6) Junk Rating*	*(7) Short-term Funding*	*(8) Funding Cost Volatility*	*(9) Listed Firms*	*(10) Equity Ownership*
Test Variables:										
SSM Treated	-0.009	-0.009***	-0.008***	-0.010***	-0.008*	-0.002	-0.006	-0.008*	0.002	0.001
	(0.266)	(0.004)	(0.001)	(0.000)	(0.061)	(0.577)	(0.284)	(0.064)	(0.659)	(0.765)
SSM Treated*AQR	0.140***	0.007***	0.006***	0.007***	0.008***	0.026**	0.077**	0.046*	0.037	0.048*
	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.040)	(0.017)	(0.053)	(0.188)	(0.054)
SSM Treated*Split	0.000	0.007	-0.001	0.002	0.002	0.011	0.005	0.001	-0.007	-0.016***
	(0.959)	(0.369)	(0.797)	(0.748)	(0.745)	(0.379)	(0.566)	(0.950)	(0.277)	(0.005)
SSM Treated*AQR*Split	-0.132***	0.062*	0.083**	0.078**	0.048*	0.147***	-0.040	-0.003	-0.028	-0.038
	(0.009)	(0.058)	(0.019)	(0.026)	(0.054)	(0.001)	(0.372)	(0.923)	(0.324)	(0.127)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm
N	8,300	8,300	8,300	8,300	8,300	2,438	1,310	6,147	7,653	7,105
Adj. R^2	0.831	0.830	0.830	0.830	0.829	0.877	0.860	0.823	0.829	0.831

(continued)

Table 2.5 (continued)
Panel C: Coverage ratio

	Institutional Setup					*Market Monitoring*				
Coverage Ratio as Dependent Variable	*(1) Regulatory Quality*	*(2) Recession*	*(3) Distrust EU*	*(4) Distrust ECB*	*(5) Anti-EU Party*	*(6) Junk Rating*	*(7) Short-term Funding*	*(8) Funding Cost Volatility*	*(9) Listed Firms*	*(10) Equity Ownership*
Test Variables:										
SSM Treated	-0.068*	-0.011	-0.074*	-0.097**	-0.099**	0.027	-0.056	-0.016	0.026	0.008
	(0.086)	(0.715)	(0.095)	(0.034)	(0.016)	(0.556)	(0.306)	(0.764)	(0.537)	(0.815)
SSM Treated*AQR	0.379**	0.038***	0.052***	0.051***	0.057***	-0.136	0.006	0.053	-0.170	0.003
	(0.023)	(0.000)	(0.000)	(0.000)	(0.000)	(0.431)	(0.971)	(0.783)	(0.289)	(0.982)
SSM Treated*Split	0.042	-0.039	0.061	0.063	0.118**	-0.181*	-0.021	-0.020	-0.067	-0.085
	(0.395)	(0.453)	(0.265)	(0.251)	(0.023)	(0.075)	(0.741)	(0.759)	(0.194)	(0.189)
SSM Treated*AQR*Split	-0.345**	0.036	-0.031	0.219	-0.108	0.888**	0.153	-0.086	0.222	0.054
	(0.038)	(0.866)	(0.860)	(0.111)	(0.514)	(0.018)	(0.507)	(0.739)	(0.164)	(0.672)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm
N	6,069	6,069	6,069	6,069	6,069	1,943	591	4,358	5,694	5,502
Adj. R^2	0.709	0.709	0.709	0.710	0.710	0.557	0.853	0.707	0.704	0.711

(continued)

Table 2.5 (continued)
Panel D: NPL ratio

	Institutional Setup					*Market Monitoring*				
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
NPL Ratio as Dependent Variable	*Regulatory Quality*	*Recession*	*Distrust EU*	*Distrust ECB*	*Anti-EU Party*	*Junk Rating*	*Short-term Funding*	*Funding Cost Volatility*	*Listed Firms*	*Equity Ownership*
Test Variables:										
SSM Treated	-0.034***	-0.014*	-0.021	-0.024**	-0.019***	0.003	-0.006	-0.012*	0.005	0.001
	(0.003)	(0.073)	(0.106)	(0.032)	(0.009)	(0.387)	(0.424)	(0.054)	(0.493)	(0.817)
SSM Treated*AQR	0.132***	0.013***	0.014***	0.016***	0.015***	0.025*	0.063***	0.046	0.018	0.033*
	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.092)	(0.007)	(0.124)	(0.317)	(0.091)
SSM Treated*Split	0.022	-0.014	-0.000	0.003	-0.000	0.003	-0.017	-0.015	-0.032***	-0.036***
	(0.120)	(0.342)	(0.991)	(0.814)	(0.994)	(0.817)	(0.333)	(0.393)	(0.002)	(0.002)
SSM Treated*AQR*Split	-0.119**	0.070**	0.057**	0.075**	0.035	0.116*	-0.009	0.021	-0.000	-0.015
	(0.015)	(0.032)	(0.046)	(0.042)	(0.223)	(0.052)	(0.879)	(0.668)	(0.999)	(0.456)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm
N	6,097	6,097	6,097	6,097	6,097	1,956	592	4,382	5,717	5,516
Adj. R^2	0.911	0.911	0.911	0.911	0.911	0.938	0.927	0.909	0.914	0.917

(continued)

Table 2.5 (continued)

Panel E: Stock liquidity

Log(Bid-Ask Spread) as Dependent Variable	*Institutional Setup*					*Market Monitoring*				
	(1) Regulatory Quality	*(2) Recession*	*(3) Distrust EU*	*(4) Distrust ECB*	*(5) Anti-EU Party*	*(6) Junk Rating*	*(7) Short-term Funding*	*(8) Funding Cost Volatility*	*(9) Listed Firms*	*(10) Equity Ownership*
Test Variables:										
SSM Treated	-0.086	0.159	0.140	-0.311	-1.285***	-0.214***	0.018	-0.219**	-0.076	-0.170
	(0.497)	(0.266)	(0.842)	(0.662)	(0.002)	(0.002)	(0.856)	(0.037)	(0.514)	(0.154)
SSM Treated*AQR	-0.832*	-1.120*	-3.287***	-0.716*	6.853	-0.254*	-0.335**	-0.371*	-0.586	-0.485
	(0.057)	(0.082)	(0.000)	(0.089)	(0.205)	(0.065)	(0.033)	(0.076)	(0.103)	(0.114)
SSM Treated*Split	0.143	-0.291	-0.209	0.290	1.149***	0.448***	0.002	0.555***	0.362	0.455***
	(0.433)	(0.115)	(0.767)	(0.687)	(0.009)	(0.003)	(0.992)	(0.000)	(0.109)	(0.008)
SSM Treated*AQR*Split	-0.080	0.310	2.713***	-0.143	-7.662	-2.162***	-2.021***	-2.074***	-1.648***	-1.928***
	(0.932)	(0.690)	(0.000)	(0.783)	(0.155)	(0.000)	(0.000)	(0.000)	(0.006)	(0.005)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm, Country* Month	Firm, Country* Month	Firm, Country* Month	Firm, Country* Month	Firm, Month	Firm, Country* Month	Firm, Country* Month	Firm, Country* Month	Firm, Country* Month	Firm, Country* Month
N	5,565	5,565	5,417	5,417	6,111	2,464	4,517	5,142	5,417	5,138
Adj. R^2	0.922	0.923	0.923	0.923	0.814	0.929	0.929	0.926	0.923	0.927

Table 2.5, Panels A-E show the results from regressions investigating the differential effect of SSM supervision, depending on the magnitude of the AQR impact, on banks' loan loss provision ratio (Panel A), loan loss allowance ratio (Panel B), non-performing loan ratio (Panel C), coverage ratio (Panel D) and the logarithm of monthly median quoted daily Bid-Ask Spread (Panel E), including interaction terms with a set of bank and country-specific binary indicator variables as defined in Appendix B. The sample in Panel A-D comprises 1,678 treatment and control banks. All control variables in Panel A-D are identical to Table 3, except for the regression in column (7) of Panel A, which excludes ΔNPL (without any change in results) to preserve the sample size. The sample in Panel E comprises 104 treatment and control banks with publicly listed equity. All control variables in Panel E are identical to Table 4. We include year and firm fixed effects in the regressions in Panel A-D, and (country-) month and firm fixed effects in the regressions of Panel E, but do not report the coefficients. The table reports OLS coefficient estimates and (in parentheses) p-values based on robust standard errors clustered by bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

2.4.4. Timeliness of the loan loss provision

We conclude our analysis with a closer examination of the mechanisms that drive the observed increase in perceived transparency following the introduction of the SSM and the AQR disclosures. In particular, prior literature suggests that a primary determinant of bank transparency is the timeliness of loan loss reporting (Beatty and Liao, 2014; Bushman, 2014; Bushman and Williams, 2015). Our analysis in this section borrows from prior literature and is centered on the association between loan loss provisions and changes in current and future non-performing loans as a proxy for the timeliness of the provisions (Bhat, Ryan, and Vyas, 2018; Gebhardt and Novotny-Farkas, 2011; Nichols, Wahlen and Wieland, 2009). Consistent with the evidence from the market liquidity tests, we expect that the change in the timeliness of banks' provisioning choice is positively associated with the magnitude of the disclosed AQR adjustment to their loan loss provisions. We estimate the following model:

$$LLP_t = \beta_0 + \beta_1\ SSM\_Treated + \beta_2\ SSM\_Treated*AQR + \beta_3\ SSM\_Treated*\Delta NPL_t + \beta_4\ SSM\_Treated*AQR*\Delta NPL_t + \beta_5\ AQR*\Delta NPL_t + \beta_6\ SSM\_Treated*\Delta NPL_{t+1} + \beta_7\ SSM\_Treated*AQR*\Delta NPL_{t+1} + \beta_8\ AQR*\Delta NPL_{t+1} + \beta_9\ \Delta NPL_t + \beta_{10}\ \Delta NPL_{t-1} + \beta_{11}\ \Delta NPL_{t+1} + \sum \beta_i\ Controls + \sum \beta_j\ Fixed\ Effects + \varepsilon \qquad (4)$$

We regress current loan loss provisions scaled by total gross loans (LLP_t) on the change in non-performing loans over the previous financial year (ΔNPL_t) and the change in non-performing loans over the following year (ΔNPL_{t+1}). We interact both variables with *SSM_Treated* and *AQR*, defined as in model (1), to estimate the change in how timely managers incorporate information about delinquent loans in the loan loss provision around the supervisory AQR disclosures. In addition to the control variables specified in model (1), we include the lagged loan loss allowance ratio (*LLA*) to capture banks' prior loan loss accruals (Nichols et al., 2009) and changes in non-performing loans from year t–2 to t–1 (ΔNPL_{t-1}; Nicoletti, 2018) to control for managers' past expectations about loan losses.

Our results in Table 2.6, columns (1) and (2), generally support our prediction. While participation in the SSM per se appears to be associated with a decrease in timely loan loss provisioning, we observe an increase in timeliness corresponding to the magnitude of the disclosed AQR adjustments, which however is significant only for projection of losses from contemporary changes in non-performing loans.

Table 2.6 Timeliness of loan loss provisions

	(1)	*(2)*
Dependent Variable:	*LLP*	*LLP*
Test Variables:		
SSM Treated	-0.007**	-0.006*
	(0.037)	(0.052)
SSM Treated*AQR	0.021***	0.004
	(0.000)	(0.709)
SSM Treated*ΔNPL_t	-0.141**	-0.174***
	(0.011)	(0.009)
SSM Treated*AQR*$\Delta \mathrm{NPL}_t$	1.625***	2.469***
	(0.000)	(0.002)
Control Variables:		
AQR*ΔNPL_t	-0.007	-0.488**
	(0.156)	(0.043)
SSM Treated* ΔNPL_{t+1}		0.196
		(0.263)
SSM Treated*AQR*ΔNPL_{t+1}		-0.767
		(0.286)
AQR*ΔNPL_{t+1}		-0.301**
		(0.045)
ΔNPL_t	0.074***	0.075***
	(0.000)	(0.000)
ΔNPL_{t-1}	0.050***	0.050***
	(0.000)	(0.000)
ΔNPL_{t+1}	-0.011	-0.011
	(0.434)	(0.417)
LLA	0.006	0.006
	(0.390)	(0.387)
Tier 1	0.030***	0.030***
	(0.002)	(0.002)
Size	0.002	0.002
	(0.370)	(0.387)
Cost-to-Income	-0.010***	-0.010***
	(0.000)	(0.000)
RoA	-0.190***	-0.187***
	(0.000)	(0.000)
GDP	-0.038	-0.040*
	(0.121)	(0.088)
Risk-weighted Assets	0.001	0.001
	(0.753)	(0.809)
Fixed Effects	Year, Firm	Year, Firm
N	3,298	3,298
Adj. R^2	0.664	0.664

Table 2.6 shows regression results for the effect of SSM supervision, depending on the magnitude of the AQR impact, on the timeliness of banks' loan loss provision. *SSM Treated* is a binary indicator variable that takes the value of '1' beginning in the first year that a treatment bank falls under SSM supervision. *AQR* is the impact of the AQR adjustment on the loan loss provision (additionally required loan loss provisions) scaled by the amount of the loan loss allowance in the year preceding the AQR. All other variables are defined in Appendix B. All bank-level control variables are lagged by one year. We include year and firm fixed effects in the regressions, but do not report the coefficients. We winsorize all variables at the 1% and at the 99% level. The table reports OLS coefficient estimates and (in parentheses) *p-values* based on robust standard errors clustered by bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

2.5. Conclusion

When the ECB became the responsible supervisor for major Eurozone banks under the European Single Supervisory Mechanism in 2014, it publicly disclosed the results of an extensive Asset Quality Review that revealed adjustments to the financial statements of these banks. Although these adjustments were mostly nonbinding for future bank reporting, they indicate a shift in the supervisory preferences about the reporting of banks' portfolio quality relative to the national bank supervisors previously responsible. We use this setting to examine whether banks' reporting behavior and perceived transparency changed around the shift in supervisory institutions and the release of the supervisory disclosures. In addition, we explore the role of supervisory enforcement and market monitoring in this process.

The supervisory AQR disclosures reveal that, on average, the ECB favored a higher level of reporting conservatism than the local authorities, with the adjustments representing an increase in the loan loss allowance for the majority of affected SSM banks. Over the following reporting periods, we observe that banks with greater AQR adjustments increased their level of loan loss provisions and classified more loans as non-performing relative to other SSM banks. In addition, banks with large adjustments in the AQR also experienced a significant increase in stock liquidity after the SSM introduction, indicating a higher level of perceived reporting transparency.

In a series of cross-sectional tests, we explore potential determinants of these changes. We find that the adjustments in banks' reporting behavior vary with institutional characteristics of countries' supervisory infrastructure that likely determine enforcement intensity. More specifically, the increase in reporting conservatism is particularly pronounced where the prior national supervisors were likely to be captured by political interest, with the takeover of supervisory responsibility by the ECB constituting an increase in supervisory independence. On the other hand, reporting changes are less pronounced when the overall regulatory quality of the previous national supervisor had already been high. We attribute this finding to the joint effect of prior leniency being explicit regulatory policy (instead of supervisory failure) and a higher bargaining power of the national supervisor relative to the ECB, which initially had to rely extensively on local supervisory resources. Together, these results point at the important role of supervisory reporting preferences (beyond simple compliance with given accounting standards) and institutional enforcement in shaping financial reporting characteristics.

However, we find that the observed increase in stock liquidity is associated with the intensity of potential market monitoring as indicated by firm-level funding structure and country-level capital market sophistication rather than with the change in supervisory enforcement. These findings suggest that the supervisory AQR disclosures can facilitate transparent reporting through the initiation of market discipline. Viewed collectively, our findings provide a textured picture of the effects of public enforcement and supervisory disclosures on firm transparency. While supervisory reporting preferences are an important determinant of accounting outcomes within a given accounting framework, supervisory disclosures can affect transparency beyond the implementation of a certain supervisory policy.

The European AQR setting offers unique features, but is also subject to certain limitations. Perhaps most importantly, our evidence on the channels through which reporting behavior and market liquidity are affected comes from purely cross-sectional variation and therefore remains largely descriptive. Moreover, the ECB only provides the supervisory disclosures for a specific group of large and systemically relevant banks. While we attempt to mitigate a potential selection bias through our sample composition and matching procedure, our setting does not allow any statements about the generalizability of our results for smaller banks that tend to receive less public scrutiny. We leave these questions for future research.

2.6. Appendix B: Variable definitions

Variable	Definition	Data Source
Firm-level Variables		
Tier 1	Tier 1 capital / total risk-weighted assets	S&P Global MI
Size	Ln(total assets)	S&P Global MI
Cost-to-Income Ratio	Operating expenses / operating income	S&P Global MI
RoA	Pre-provision net income / total assets	S&P Global MI
Risk-weighted Assets	Risk-weighted assets / total assets	S&P Global MI
ΔNPL	Non-performing loans / Non-performing loans$_{t-1}$	
Loan loss provisions (LLP) Ratio	Loan loss provision / total gross loans	S&P Global MI
Loan loss allowance (LLA) Ratio	Loan loss allowance / total gross loans	S&P Global MI
Non-performing loans (NPL) Ratio	Non-performing loans / total gross loans	S&P Global MI
Coverage Ratio	Loan loss allowance / non-performing loans	S&P Global MI
Junk Rating	Binary variable that takes the value of '1' for banks with a S&P rating below BBB-	S&P Global MI
Short-term Funding	Binary variable that takes the value of '1' for firms with above median short-term deposit ratio (as of 2013)	S&P Global MI
Funding Cost Volatility	Binary variable that takes the value of '1' for firms with above median funding cost volatility between 2011-2013	S&P Global MI
AQR Adjustment	AQR adjustment on the loan loss provision (additionally required loan loss provisions) / loan loss allowance in 2013	ECB & S&P Global MI
Liquidity Variables		
Bid-Ask Spread	Monthly median of the quoted spread between the bid and ask price	Datastream
Abs(Abnormal Stock Return)	Absolute abnormal monthly stock return	Datastream
Market Value	Monthly median of daily market value	Datastream
Share Turnover	Monthly median of daily share turnover	Datastream
Return Variability	Monthly standard deviation of daily returns	Datastream
Country Variables		
Distrust EU	Binary variable that takes the value of '1' for countries with below median trust in the ECB as of 2014	Eurobarometer Survey
Distrust ECB	Binary variable that takes the value of '1' for countries with below median trust in the EU as of 2014	Eurobarometer Survey
Anti-EU Party	Binary variable that takes the value of '1' for countries with at least one Anti-EU party that is represented in the European Parliament with at least 5% of the seats within the country as of 2014	Manifesto Project, Manual Collection
Recession	Binary variable that takes the value of '1' for all countries with negative GDP growth in the two years before the SSM introduction (2011 and 2012)	World Bank
GDP	Yearly Growth in Gross Domestic Product	World Bank
Regulatory Quality	Binary variable that takes the value of '1' for countries with above median regulatory quality over the sample period from 2011-2017	Kaufmann, Kraay, and Mastruzzi, (2011)
Equity Ownership	Binary variable that takes the value of '1' for countries with above median ratio of household equity ownership (2008-2010)	Christensen, Maffet and Vollon (2019)
Listed Firms	Binary variable that takes the value of '1' for countries with above median ratio of listed firms to GDP in 2014	World Bank

2.7. Appendix C: Entropy balancing

	(2)	(4)	(6)	(8)
Dependent Variable:	*LLP Ratio*	*LLA Ratio*	*Coverage Ratio*	*NPL Ratio*
Test Variables:				
SSM Treated	-0.003	0.002	-0.028	0.012*
	(0.245)	(0.567)	(0.426)	(0.067)
SSM Treated*AQR	0.013*	0.043**	-0.047	0.036**
	(0.052)	(0.012)	(0.741)	(0.023)
Control Variables:				
ΔNPL	0.077***			
	(0.003)			
Tier 1	-0.000	-0.000	0.003	-0.001
	(0.820)	(0.329)	(0.455)	(0.365)
Size	0.010***	-0.007	-0.130	0.020
	(0.008)	(0.243)	(0.125)	(0.175)
Cost-to-Income	-0.000	0.000	0.001	0.000***
	(0.687)	(0.557)	(0.448)	(0.006)
RoA	0.065	0.584***	1.009	1.312***
	(0.399)	(0.004)	(0.415)	(0.000)
GDP	-0.001*	0.001**	0.006	-0.000
	(0.094)	(0.032)	(0.162)	(0.640)
Risk-weighted Assets	0.000***	0.000	-0.002	0.001
	(0.006)	(0.162)	(0.179)	(0.119)
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm
N	4,122	6,085	4,329	4,353
Adj. R^2	0.636	0.843	0.835	0.930

Appendix C replicates Table 3 using an entropy balanced sample. We use the entropy balancing approach to reweight the observations in our sample in a way such that the distribution of values of the control variables in the treatment group is as similar as possible to the distribution in the control group along the first three moments (mean, variance and skewness). We include year and firm fixed effects in the regressions, but do not report the coefficients. We winsorize all variables at the 1% and at the 99% level. The table reports OLS coefficient estimates and (in parentheses) *p-values* based on robust standard errors clustered by bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Chapter 3

Legal Efficiency and Non-Performing Loans along the Economic Cycle

"Going into the next downturn with such a high stock of NPLs is simply not an option. And NPLs are not just concentrated in one or two European countries; they are spread across a number of countries and a high number of banks. NPLs remain a European issue, no matter where the banks holding them are located."

Danièle Nouy, 23/11/2018, in a speech to the European Banking Federation

3.1. Introduction

The global financial crisis and the recent economic fallout due to the corona virus focused a spotlight on the resilience of banks' balance sheets and in particular banks' non-performing loans (NPLs). If a bank's borrower gets into arrears, e.g. during economic downturns, the loan is recorded as non-performing[27] resulting in a higher risk-weight[28]. In addition, the bank might be required to book a provision against the potential loan loss that impairs net income and regulatory capital. As a consequence, banks cannot utilize their capital for productive lending and face higher funding costs due to higher risk-weights. This has severe economic consequences, as high NPL-levels can impair bank stability (Berger and DeYoung, 1997; Whalen, 1991) and hamstring bank lending and ultimately economic activity (Barseghyan, 2010). Therefore, a quick work-out of banks' non-performing loans, in particular after economic downturns, is key to foster lending and maintain bank stability.

[27] Typically, banks are required to record a loan as non-performing if the borrower is 90-days past due, and the borrower is unlikely to pay the obligation back in full (ECB, 2017).

[28] Under Basel 3, NPLs are subject to a risk weight of 150 percent when applying the standardized approach.

After the great financial crisis and the sovereign debt crisis total NPLs in the Eurozone increased up to 958 billion Euro in December 2014. While NPLs declined to 688 billion Euro in March 2018, the level of NPLs is still much higher than before the great financial crisis although most European countries were in an economic growth phase (ECB, 2019). Therefore, regulators and supervisors continuously highlight the importance of NPLs and made NPL resolution a top priority in the recent years (e.g., IMF, 2015; ECB, 2016, 2017; ECOFIN, 2017). However, in order to determine an adequate policy response, it is first necessary to understand the intertemporal and cross-country determinants of NPLs in the first place.

The existing evidence on the determinants of NPLs consistently documents a negative correlation between economic growth and NPLs (e.g., Ghosh, 2015; Salas and Saurina, 2002). Taking these studies at face value one would expect that NPLs are countercyclical to macroeconomic conditions. That is, NPLs increase in economic downturns and decrease in economic expansions. In contrast to this assumption, I observe that while all countries in Europe during the great financial crisis build up NPLs, some countries build up relatively persistent NPL stocks even within the following expansionary phases. Therefore, it seems unlikely that economic growth uniformly determines NPLs over the whole business cycle.

There are two non-mutually explanations for this phenomenon. First, it could be that bank-specific factors, such as profitability, regulatory capital or size are the main enablers of swift NPL resolution while macroeconomic factors mainly determine how NPL levels build up. Second, the resolution of NPLs could be shaped by country-specific but not growth-related factors such as legal efficiency. The conjecture that determinants of NPLs change across business cycles is further supported by anecdotal evidence from Hoshi and Kashyap (2010) who document that the nature of NPLs in Japan changed significantly over the economic cycle.

Along these lines, policymaker and regulators recognize that a successful NPL resolution strategy will include insolvency and judicial frameworks that allow cost and time efficient NPL work-outs (e.g., ECOFIN, 2017; ECB, 2016). Although countries might have similar rules for contract enforcement and insolvencies, the enforcement of these rules might still depend on the efficiency of the legal system, such as the speed and honesty of the courts. In particular, collateral enforcement rules and judicial system inefficiencies, such as weak corporate and household insolvency frameworks that lead to slow collateral recovery represent a major risk for creditors and are a notable challenge to NPL resolution (ECB, 2016).

The effect of legal efficiency on NPLs is twofold. First, efficient debt enforcement and insolvency procedures can ex ante deter loan defaults by changing the borrower's willingness to pay. Second, borrowers often secure loans with collateral. If this collateral cannot be realized by the bank due to lengthy and expensive foreclosure procedures this deters NPL resolution and limits new bank lending (Haselmann, Pistor, Vig, 2010). Against this backdrop, policymakers should carefully consider the recent initiatives made during the pandemic, such as the temporary suspension of the obligation to file for insolvency (§15a InsO) in Germany until the end of October 2020. This suspension could lead to an accumulation of insolvency filings after the end of the grace period swamping the courts.

Even in normal times, the speed and the costs of insolvency and contract enforcement procedures vary significantly across countries (Djankov La Porta, Lopez-de-Silanes and Shleifer, 2003). Only a few countries in Europe (e.g., Slovenia and Spain) have efficient and simple out-of-court insolvency and enforcement mechanisms in place. Furthermore, I expect that the influence of legal efficiency is likely not uniform over the NPL cycle. While legal efficiency is unlikely to mitigate increased loan defaults and the building up of NPL stock during economic recessions, it potentially contributes significantly to a fast NPL recovery process in the subsequent periods when economic growth picks up. Therefore, I make the following two empirical predictions:

Prediction 1: *Countries with high legal efficiency can reduce their NPLs earlier compared to countries with low legal efficiency from the beginning of an economic upturn*

Prediction 2: *High legal efficiency has an incremental negative association with NPLs during economic upturns, whereas macroeconomic and bank-specific factors mainly explain NPLs during economic downturns.*

I employ a sample from 17 different European countries to explore these questions using two sets of analyses. First, I exploit the variation in the duration of NPL cycles across countries to explore whether legal efficiency and economic growth determine the duration of NPL cycles. Therefore, I test in a proportional hazard model whether (a) legal efficiency is associated with the duration of the increasing NPL phase and (b) legal efficiency correlates with the duration until NPLs decrease from the start of an economic upturn. My findings indicate that while the duration of an increasing NPL phase is mainly associated with economic growth, the duration towards a NPL resolution from the beginning of an economic upturn is highly correlated with the efficiency of the legal procedures in place for contract enforcement and insolvencies.

To test the second prediction, and to benchmark cross-country differences in legal efficiency with firm factors, I move to the firm-level for the subsequent analyses. Using firm-level data on NPLs, I document that legal efficiency is highly correlated with NPLs even when controlling for several firm-level factors, such as profitability, regulatory capital and cost efficiency. Exploiting variation in economic cycles across countries, I further find legal efficiency to be negatively associated with NPLs in economic upturns. I confirm that this correlation is mainly confined to the duration and the costs of insolvency and contract enforcement procedures and cannot be explained by firm factors or other cross-country differences, such as supervisory power or overall regulatory quality.

I contribute to the existing literature along three dimensions. First, I acknowledge that associations with NPLs may change over the economic cycle. That is, factors that matter for NPLs during the increasing NPL phase might not be less relevant during the reduction phase of NPLs and vice versa. Although there is anecdotal evidence that the nature of NPLs can change over time (Hoshi and Kashyap, 2010), this is, to the best of my knowledge, the first paper that distinguishes between different economic and NPL cycles. Second, I contribute to the literature on the determinants of NPLs (e.g., Barth, Caprio, and Levine, 2004; Gosh, 2015) by exploring bank- and country-specific factors that potentially explain NPLs in Europe. Third, I add to the literature on the effects of cross-country differences in the institutional set-up (Djankov et al., 2003; Djankov, Hart, McLiesh, and Shleifer, 2008) by investigating whether insolvency and contract enforcement correlate with NPLs along the economic cycle.

The remainder of the paper proceeds as follows. In Section 2, I provide a survey of the literature on NPLs. Section 3 outlines the research design and describes the sample selection. In Section 4, I present the results of the cox proportional hazard analysis on the country level and the regression analysis on the firm level to explore the duration of NPL cycles. Section 5 concludes.

3.2. Literature review

The literature on the determinants of non-performing loans can be broadly categorized into studies that explore (i) country-specific (mostly macroeconomic) and, (ii) bank-specific factors. An overarching pattern across studies of macroeconomic determinants NPLs is the documented negative relationship between GDP growth and NPLs (e.g., Ghosh, 2015; Salas and Saurina, 2003; Cerulli et al., 2019; Breuer, 2006; Beck, Jakubik and Piloiu, 2013). Other macroeconomic determinants are, inter alia, exchange rates (Klein, 2013; Beck et al., 2013), foreign lending (Kauko, 2012), share prices (Beck et al., 2013), lending interest rates (Espinoza and Prasad, 2011, Louzis et al., 2011), unemployment (Ghosh, 2015; Nkusu, 2011), and house prices (Bofondi and Ropele, 2011; Ghosh, 2015). However, evidence on most associations between NPLs and macro determinants is not fully conclusive, potentially due to the limited comparability of samples (both in terms of countries and time periods) and multicollinearity issues when adding highly correlated macroeconomic growth indicators such as GDP, house prices and unemployment to multivariate models. Nevertheless, an overarching conclusion from most above mentioned studies is that economic growth in different facets (GDP, employment, house prices) seems to be negatively correlated with NPL levels. However, none of the above mentioned studies distinguishes explicitly between different periods of the business or NPL cycle.

Furthermore, the majority of the literature on NPL determinants focuses on individual countries, such as the US (Ghosh, 2015), Spain (e.g., Salas and Saurina, 2002), Italy (Bofondi and Ropele, 2011; Cucinelli, 2015; Japelli et al., 2005) Japan (Mamatzakis, Matousek and Vu, 2015), India (Ghosh, 2007), Greece (Louzis et al., 2011), the Czech Republic (Podpiera and Weill, 2008), Romania (Filip, 2014) or specific regions such as the Gulf area (Espinoza and Prasad, 2011), and eastern Europe (Klein, 2013; Agoraki, 2011) limiting comparability and generalizability.

In addition, there is evidence on the role of regulation and disclosure requirements for NPLs. Barth et al. (2004) find a weakly significant negative association between private monitoring, strict capital requirement regulations and NPLs. Similar results are documented by Agoraki et al. (2011) for supervisory power, and Breuer (2006) for off-balance sheet disclosures. In addition, D'Apice and Fiordelisi (2020) explore the effects of four enforcement reforms between 2008 and 2011 on banks NPLs. In addition, the theoretical model from Japelli, Pagano and Bianco (2005) shows that assuming and endogenous default rate, judicial efficiency helps to decrease the average default rate by fostering borrower selection ex ante. Further descriptive evidence from a sample of Italian districts between 1984 and 1998 indicates that the length of the contract enforcement process and the backlog of cases at regional courts in Italy are correlated with NPLs.

In addition to cross-country differences, several studies find bank-specific factors to be correlated with NPLs. Against this backdrop, Berger and DeYoung (1997) document that decreases in cost efficiency are reflected in higher NPLs due to excess expenditures for the monitoring of bad loans that, however, on average come along with overall worse monitoring and underwriting practices. Furthermore, their findings indicate the presence of moral hazard incentives for weakly capitalized banks that respond to asset quality deteriorations with an increase in risk-taking. Furthermore, Behr et al. (2009) and Salas and Saurina (2002) document a negative correlation between bank size and NPLs potentially resulting from better diversification opportunities. Profitability is also frequently associated with lower NPLs for instance in Greece. (Louzis et al., 2011) or in Spain (Salas and Saurina, 2002).

Overall then, several studies document that country specific and bank-specific factors matter for NPLs, however there is a lack of evidence on the association between legal efficiency and NPLs over the business cycle in Europe.

3.3. Research design and data

I evaluate the development of NPLs from two perspectives. First, I use aggregated data on NPLs within 17 Eurozone countries from the World Bank Global Financial Development Database. This database includes NPL ratios from the yearly Global Financial Stability Report published by the International Monetary Fund. I include all Eurozone countries with available information on macroeconomic growth and legal efficiency measures.

Second, I also analyze annual bank-level information from S&P Global Market Intelligence (formerly SNL Financial). In contrast to most prior research on NPLs in Europe, I build on a dataset that includes actual NPLs and not impaired loans (e.g., as provided by Bankscope). Although, impaired loans are potentially a valid proxy of NPLs, they reflect an accounting concept (e.g., IAS 39 during my sample period) with substantial discretion (e.g. Ryan and Liu, 2006) compared to NPLs which are a supervisory construct (Regulation (EU) No 680/2014). Furthermore, while the ECB definition of NPLs includes all loans that are 90-days past due and the debtor is unlikely-to-pay (ECB 2017), the accounting definition (IAS 39) of impaired loans requires a dedicated 'trigger event' indicating that the loan will not be repaid in full. As a consequence, the definition of NPLs is much broader than the concept of impaired loans. Therefore, relying on impaired loans as a proxy for NPLs can lead to wrong conclusions if specific reporting incentives are embedded in the reporting of impaired loans.

The final firm-level sample includes all banks that have available data on the macro-level variables (GDP and legal efficiency) and information on bank-level control variables (tier 1 regulatory capital, total assets, loans, cost-to-income, return on assets). The sample period for both data sets spans the period from 2007 to 2016. I end up with a maximum of 157 country-level observations and 14,151 firm-level observations.

In my first set of analyses I employ the country-level dataset to answer the question whether legal efficiency and economic growth influence the duration of NPL cycles. I test this prediction by employing a proportional hazard model to measure the influence of economic growth and legal efficiency on (i) the probability of reaching the maximum NPL level as a function of time since the start of the sample and (ii) the probability of achieving a decrease in NPLs as a function of time since the start of an economic growth phase. Cox models are frequently employed in accounting, finance and economics to estimate the duration until a specific event while accounting for censoring due to incomplete information about individuals or firms (e.g., Bischof and Daske, 2013; Whited, 2006; Maennasoo and Mayes, 2009; Meyer, 1990). I estimate the following Cox proportional hazard model:

$$\mathrm{h(t)} = h_0(t) + \beta\ e^{\beta X_{it}} \tag{1}$$

Where h(t) is the hazard function and t is the time to the event (either the highest level of NPLs or when a decrease in NPLs was achieved). $h_0(t)$ is the baseline hazard function. X_{it} is a column vector including GDP growth and legal efficiency. I collect data on GDP growth from the World Bank. Furthermore, I employ data on legal efficiency measures related to insolvency and contract enforcement procedures from the annual World Bank Doing Business report (Djankov et al., 2003; Djankov et al., 2008). The World Bank collects this data from own research, supplemented with data from central banks and the 'Economist Intelligence Unit'. I cluster standard errors by country (Petersen, 2009).

In the second set of analyses, I employ bank-level data from S&P Global Market Intelligence to explore whether macroeconomic, bank-specific or cross-country differences in legal efficiency are associated with NPLs over the economic cycles. I start with an estimation of the following fixed effect OLS model over the sample period from 2006 to 2016:

$$NPL\ Ratio = \beta_0 + \beta_1\ Legal\ Efficiency + \beta_2\ GDP + \beta_3\ Recovery + \beta_4\ Legal\ Efficiency * Recovery + \beta_5\ GDP * Recovery + \sum \beta_i\ Controls + \sum \beta_j\ Fixed\ Effects + \varepsilon \quad (1)$$

The dependent variable *NPL Ratio* is the percentage of non-performing loans divided by gross loans. There are four main variables of interest. *GDP* as the annual gross domestic product growth rate in the respective country obtained from the World Bank and *Legal Efficiency* that stands for a vector of binary partitioning variables that capture systematic variation in legal efficiency with respect to contract enforcement and insolvency procedures. Furthermore, I explore whether GDP and Legal Efficiency have diverging effects over the economic cycle by interacting both variables with *Recovery* that stands for a binary variable that takes the value of '1' beginning from the first year a country enters an economic growth phase that lasts at least 3 years after 2009.[29]

I use two sets of proxies for *Legal Efficiency.* First, I use individual binary splits for countries that have above median *Insolvency Durations*, *Insolvency Costs, Insolvency Recovery Rates, Contract Enforcement Durations, Contract Enforcement Costs,* and C*ontract Enforcement Scores*. Second, I sum up all binary insolvency and contract enforcement measures (excluding only the enforcement score that itself captures a summary measure already) to build a composite *Legal Efficiency Score*. In addition, I employ a binary partitioning variable that takes the value of '1' for countries with an above median *Legal Efficiency Score (LE)* that I label *High Legal*

[29] I use three consecutive economic growth years as proxy for a recovery to avoid misclassifying countries as "recovering" that were affected by the sovereign debt crisis in 2011/12 shortly after the great financial crisis.

Efficiency (High LE). The base effect of these split variables is time-invariant and therefore subsumed by the firm fixed effect. *Controls* denotes the following firm-level control variables: *Size* as the natural logarithm of total assets, *RoA* as the percentage of pre-provisioning income to total assets as a measure of banks' profitability, *Tier 1* as the percentage of banks' tier 1 capital to risk-weighted assets, *Cost-Income* as the percentage of operating expense to operating income measuring banks' efficiency. *Loan Ratio* as the ratio of total gross loans to total assets. I include year- and firm-fixed effects, which account for the general time trend as well as time-invariant bank and country characteristics (e.g., the overall quality of the legal system or the development of capital markets). As such, my fixed-effects structure subsumes factors that are specific to a certain year or a particular bank. In all my tests, I draw statistical inferences based on standard errors clustered by country to adjust for correlation between banks within countries and time-series correlation within countries (Petersen, 2009).

I rely on a fixed effect model to deal with unobserved heterogeneity and omitted variables instead of a dynamic panel model with the lagged dependent variable as the I am particularly interested in the correlations between NPLs that build up with relative persistence during an economic downturn and decrease during an economic downturn. Nevertheless, I follow the approach from Ghosh (2015) and confirm that my inference is robust within a dynamic panel system-GMM estimation including lagged NPLs as explanatory variable (Arellano and Bover, 1995; Blundell and Bond, 1998).[30]

[30] Furthermore, as the fixed effect estimator brackets the true effect (Guyan, 2001), I follow the recommendation from Angrist and Pischke (2008) and rely on a fixed effect model for my analyses.

3.4. Empirical results

3.4.1. Descriptive statistics

I start with *a* descriptive analysis of NPLs across countries. Figure 3.1 plots the yearly NPL ratios of countries with high and low legal efficiency. The figure illustrates that on average countries follow a similar NPL growth trajectory until 2013 regardless of their legal efficiency. However, countries with high legal efficiency reach their highest NPL level in 2013, while still rising for countries with low legal efficiency.

Figure 3.1 NPL Ratios and GDP Development for High vs. Low Legal Efficiency Countries

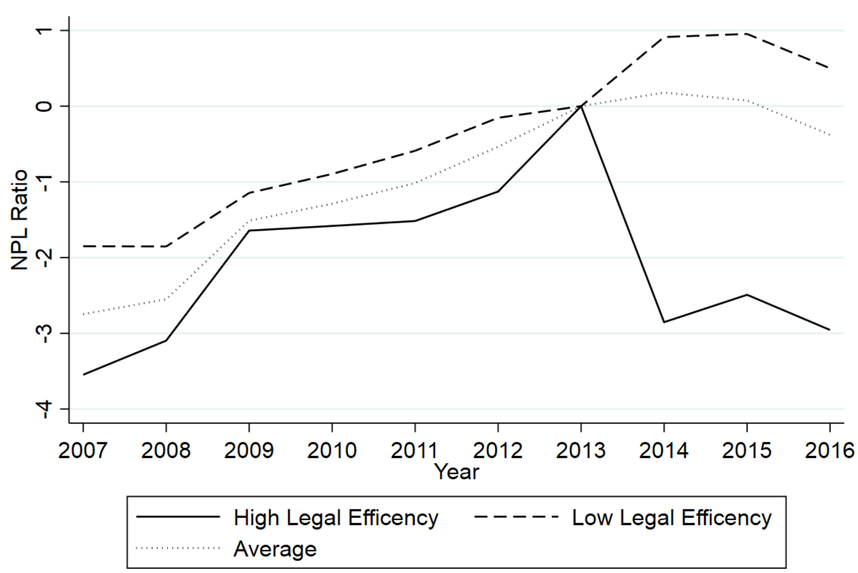


Figure 3.1 shows the NPL Ratios development over the sample period from 2007-2016 for high and low legal efficiency countries. NPL Ratios are normalized to zero in 2013.

An obvious concern from this descriptive observation is that the NPL development could be simply a reflection of different economic growth patterns across countries that I capture with the legal efficiency measure. However, when depicting GDP growth by legal efficiency in Figure 3.2, I document relatively similar average economic growth patterns across these two sets of countries. From this descriptive analyses, I conclude that while both high and low legal efficiency countries follow similar patterns during the buildup phase of the NPL cycle that is likely determined by economic developments, countries that achieve significant reductions in NPLs are characterized by efficient insolvency and enforcement procedures that come into play during economic growth periods.

Figure 3.1. GDP Development for High vs. Low Legal Efficiency Countries

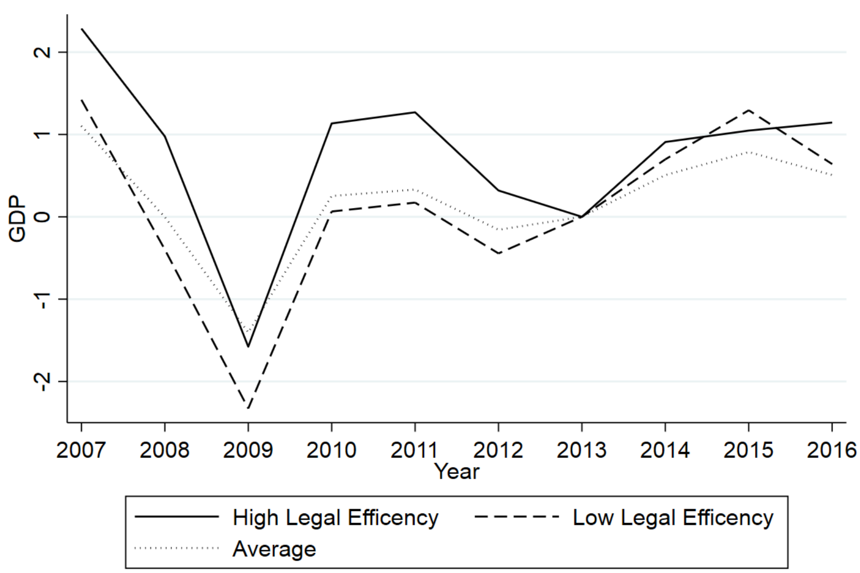


Figure 3.2 shows the GDP growth development over the sample period from 2007-2016 for high and low legal efficiency countries. GDP growth is normalized to zero in 2013.

I explore this conjecture in the next section with a more formal analysis. Additional descriptive statistics in Table 3.1, Panel A confirm that the average NPL ratio varies greatly across countries. The NPL ratio varies between 0.4% in Luxembourg and 27% in Cyprus. Table 1, Panel B shows pairwise correlations between NPLs and GDP and legal efficiency measures. Legal efficiency and in particular the enforcement duration is highly positively correlated with NPLs.

Table 3.1 Descriptive statistics and pairwise correlations on the country level

Panel A Descriptive Statistics

Country	Country-Years	Mean NPL Ratio	Mean GDP	Mean LE	High LE	Enforcement Duration	Insolvency Duration
Austria	10	2.717	1.026	3.000	1.000	1.103	1.100
Belgium	10	3.137	1.109	3.700	1.000	1.403	0.890
Cyprus	8	27.331	-0.436	2.625	1.000	2.295	1.500
Estonia	9	2.656	0.287	1.000	0.000	1.181	3.000
France	9	3.940	0.584	2.000	1.000	1.017	1.900
Germany	10	2.669	1.306	4.500	1.000	1.133	1.200
Greece	9	21.896	-3.287	1.000	0.000	3.128	2.667
Ireland	10	14.141	4.214	1.900	0.000	1.656	0.400
Italy	10	12.678	-0.542	1.000	0.000	3.297	1.800
Latvia	9	8.266	-0.223	1.556	0.000	1.115	2.167
Lithuania	9	12.826	1.193	2.222	1.000	0.796	1.833
Luxembourg	6	0.427	1.572	2.000	0.000	0.892	2.000
Malta	10	6.850	4.003	0.000	0.000	1.403	3.000
Netherlands	9	2.776	0.627	3.000	1.000	1.428	1.100
Portugal	10	9.131	-0.104	1.800	0.000	1.536	2.000
Slovenia	9	9.477	0.219	2.333	1.000	3.509	1.733
Spain	10	5.562	0.378	2.500	1.000	1.424	1.300

Panel B Pairwise Correlations

	NPL	GDP	High LE	LE	Insolvency Duration	Enforcement Duration
NPL Ratio	1.0000					
GDP	-0.0943	1.0000				
High LE	-0.1374	-0.0088	1.0000			
LE	-0.2320*	-0.0108	0.6890*	1.0000		
Insolvency Duration	0.1538	-0.1420	-0.4465*	-0.6479*	1.0000	
Enforcement Duration	0.5161*	-0.0975	-0.1742	-0.2722*	0.1666	1.0000

Table 3.1 Panel A shows descriptive statistics for all country-level variables used in our country-level tests. Panel B shows pairwise correlations for the country-level variables. * indicate statistical significance at the 5% level. All variables are defined in Appendix D.

3.4.2. What determines the duration of non-performing loan cycles?

In the first step of my empirical analysis, I run separate hazard models for two different time periods. The first time period spans from the start of the sample period in 2007 until the country reaches its highest level of NPLs. The second time period runs from the start of an economic expansion until the country decreases its NPLs for the first time. My main interest concerns the duration of the second time period to explore whether macroeconomic factors or legal efficiency can increase the likelihood that a country achieves a reduction in NPLs. Table 3.2, Panel A and B, show that the hazard of ending an increasing NPL phase is significantly higher for countries with high GDP growth while the influence of legal efficiency during the increasing NPL phase is insignificant. Panel A, column (3) shows the hazard ratios of ending an increasing NPL phase is 19.3% higher for a one percentage point increase in GDP growth given that the country did not end the increasing NPL phase in the years before. Panel A, Column (4)-(6), document that during economic expansions a higher GDP growth still significantly increases the hazard of entering a decreasing NPL phase. However, the hazard ratio for high legal efficiency countries is almost 5 times as high compared to low legal efficiency countries documenting a substantial positive association between legal efficiency and the likelihood of achieving a NPL decrease.

I continue the analyses by exploring whether the higher hazard of getting into a NPL reduction phase is related to inefficiencies in insolvency or contract enforcement procedures. In Table 3.2, Panel C, Column (1)-(3) I first document that the duration of insolvency and contract enforcement procedures is not associated with the duration of an increasing NPL phase per se. However, both the duration of insolvency and contract enforcement procedures significantly reduce the hazard of getting to a NPL reduction phase from the start of an economic upturn.

Table 3.2 Influence of legal efficiency and GDP on the duration of NPL cycles

Panel A: Hazard Ratios for Legal Efficiency and GDP

	Duration of NPL Increase			*Duration until NPL decrease in Recovery*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
High LE	1.687		2.190	4.544**		4.985**
	(0.303)		(0.132)	(0.035)		(0.026)
GDP		1.142**	1.193***		1.158*	1.198**
		(0.018)	(0.001)		(0.067)	(0.012)
N	133	133	133	26	26	26

Panel B: Hazard Ratios for Enforcement Duration, Insolvency Duration, and GDP

	Duration of NPL Increase			*Duration until NPL decrease in Recovery*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Insolvency Duration	0.988		1.023	0.716		0.602**
	(0.947)		(0.907)	(0.374)		(0.021)
Enforcement Duration		0.876	0.872		0.178***	0.132***
		(0.617)	(0.623)		(0.005)	(0.003)
GDP	1.143**	1.128**	1.126**	1.180	1.104	1.102*
	(0.011)	(0.025)	(0.019)	(0.109)	(0.107)	(0.061)
N	126	126	126	25	25	25

Table 3.2 shows results from cox proportional hazard models reporting the effect of legal efficiency and economic growth on the duration of the two different phases of the NPL cycle. *High LE* is a binary variable that takes the value of '1' if the country is above the median legal efficiency of all countries in that year. *GDP* is the yearly GDP growth. All other variables are defined in Appendix D. We winsorize all variables at the 1% and at the 99% level. The table reports hazard ratios and (in parentheses) *p-values* based on robust standard errors clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Taken together, the country-level analysis provides first indications that legal efficiency measures are significantly associated with the duration until NPLs decrease from the start of an upturn, while economic growth determines how NPLs build up during recessions. In order to benchmark these findings against the influence of bank-specific factors, I continue in the next step with an analysis on the bank level.

3.4.3. Country-level factors versus bank-specific determinants of NPLs

I start the bank-level analysis with a correlation analysis in Table 3.3. Panel B shows that NPLs are negatively correlated with legal efficiency, GDP, profitability, and tier 1 capital while positively correlated with size, the loan ratio, and the cost-income ratio. I explore these correlations more formally estimating the fixed effect OLS regression from model (2) in, Table 3.4. Column (1) indicates that banks in high legal efficiency countries have on average 1.68% lower NPL ratios compared to banks in low legal efficiency countries (p-value<0.01). Furthermore, in Column (4), I document that the negative association of legal efficiency is solely confined to expansion periods. The coefficient on *High LE*Recovery* documents that banks in high legal efficiency countries have on average a 6.6% lower NPL ratio (p-value<0.02) during economic upturns compared to low legal efficiency countries. In addition, I find that during economic recovery periods banks have on average 2.5% higher NPL ratios (p-value<0.03). The coefficient signs on my control variables show positive correlations between profitability, loan ratios, cost-income ratios[31], tier 1 ratios and NPL ratios.

[31] This result is in favor of the bad luck hypothesis from Berger and DeYoung (1998). Under the bad luck hypothesis increases in problem loans are caused by exogenous events such as an economic downturn and subsequently require extra expenses for managing these exposures. Therefore, the additional expenses for NPL management create an impression of higher cost-to-income ratios (and hence, lower cost efficiency) for banks that put substantial effort in the resolution of NPLs.

Table 3.3 Descriptive statistics on the bank level

Panel A Descriptive Statistics

Country	Banks	Bank-Years	Mean Size	Mean. Loan Ratio	Mean Cost-Income	Mean Tier 1	Mean RoA	Mean NPL
Austria	43	248	19.201	0.585	67.731	10.276	0.421	8.787
Belgium	11	87	19.317	0.532	54.975	15.994	0.719	3.335
Estonia	5	35	11.037	0.408	219.502	14.132	-5.690	8.228
Finland	75	487	10.274	0.788	72.852	65.493	0.766	0.937
France	85	518	18.312	0.467	47.071	18.287	0.036	3.560
Germany	1562	8187	14.419	0.546	70.308	18.390	0.133	3.552
Greece	12	80	17.724	0.667	45.694	10.198	1.113	20.750
Ireland	16	86	16.499	1.040	39.084	12.232	-5.898	14.106
Italy	558	3467	12.887	0.573	68.214	14.316	0.099	13.732
Latvia	7	21	15.500	0.589	39.182	40.167	2.242	8.891
Lithuania	6	26	14.343	0.562	48.412	12.122	1.405	19.264
Luxembourg	14	84	16.337	0.195	81.420	13.652	0.541	5.371
Malta	12	74	14.146	0.000	37.923	36.830	1.077	9.722
Netherlands	24	143	17.167	0.630	66.667	16.215	0.235	5.283
Portugal	38	191	11.880	0.484	64.036	27.638	-0.094	7.769
Slovenia	9	60	15.571	0.712	53.974	8.632	0.223	17.992
Spain	67	357	13.390	0.023	65.579	61.373	0.631	6.465

Panel B Pairwise Correlations

	NPL Ratio	Size	Loan Ratio	Cost-Income	Tier 1	RoA	GDP	High LE	Recovery
NPL Ratio	1.0000								
Size	0.0249*	1.0000							
Loan Ratio	0.0407*	0.0009	1.0000						
Cost-Income	0.0116	-0.1625*	-0.0274*	1.0000					
Tier 1	-0.0423*	-0.1369*	-0.1091*	0.0785*	1.0000				
RoA	-0.2155*	0.0029	-0.0316*	-0.3064*	0.0250*	1.0000			
GDP	-0.2263*	-0.0484*	-0.0176	0.0274*	-0.0254*	0.0839*	1.0000		
High LE	-0.5665*	-0.1223*	-0.0166	0.0389*	-0.0604*	0.0358*	0.3338*	1.0000	
Recovery	-0.2757*	-0.1347*	-0.0512*	0.0588*	-0.0148	0.0222*	0.3442*	0.5249*	1.0000

Table 3.3 Panel A shows descriptive statistics for all firm-level variables used in our bank-level tests. Panel B shows pairwise correlations for the bank-level and country-level variables. * indicate statistical significance at the 5% level. All variables are defined in Appendix D.

Table 3.4 Legal Efficiency along the economic cycle and NPL ratios

	(1)	*(2)*	*(3)*	*(4)*
Dependent Variable:	*NPL Ratio*	*NPL Ratio*	*NPL Ratio*	*NPL Ratio*
Test Variables:				
High LE	-1.681***		-0.955	2.285
	(0.002)		(0.209)	(0.134)
GDP		0.547	0.526	0.362**
		(0.127)	(0.152)	(0.032)
Recovery				2.562**
				(0.021)
High LE * Recovery				-6.634**
				(0.015)
GDP * Recovery				-0.045
				(0.773)
Control Variables:				
Size	-0.065	0.221	0.181	-0.248
	(0.875)	(0.569)	(0.656)	(0.623)
Loan Ratio	-0.393*	-0.380*	-0.375*	-0.319**
	(0.065)	(0.056)	(0.054)	(0.019)
Cost-Income	-0.016**	-0.018***	-0.018***	-0.014**
	(0.011)	(0.008)	(0.008)	(0.015)
Tier 1	-0.053**	-0.047*	-0.047*	-0.039
	(0.045)	(0.057)	(0.054)	(0.111)
RoA	-0.537*	-0.584*	-0.582*	-0.521*
	(0.068)	(0.054)	(0.054)	(0.064)
Constant	5.856	-0.914	0.288	5.621
	(0.241)	(0.848)	(0.958)	(0.382)
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm
SE Clustered by	Country	Country	Country	Country
Observations	14,151	14,151	14,151	14,151
R-squared	0.129	0.150	0.151	0.249
Adjusted R-squared	0.128	0.149	0.150	0.248

Table 3.4 shows regression results for the effect of legal efficiency, economic growth and bank-specific factors on the level of banks' non-performing loans ratio. *High LE* is a binary variable that takes the value of '1' if the country is above the median legal efficiency of all countries in that year. *GDP* is the yearly GDP growth. *Recovery* is a binary variable that takes the value of '1' beginning in the first year that the country enters a period of three years consecutive GDP growth. All other variables are defined in Appendix D. We include year and firm fixed effects in the regressions, but do not report the coefficients. We winsorize all variables at the 1% and at the 99% level. The table reports OLS coefficient estimates and (in parentheses) *p-values* based on robust standard errors clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

3.4.4. The role of contract enforcement and insolvency proceedings for NPLs

I continue with a closer examination of the association between legal efficiency and NPL ratios. In particular, I study the role of insolvency and contract enforcement procedures for NPL ratios over the economic cycle. For these additional cross-sectional tests, I replace the legal efficiency indicator variable in Equation (2) with six different binary partitioning variables that measure the efficiency of insolvency resolution and contract enforcement. Table 3.5, Column (1)-(3) show that *Insolvency Duration*, I*nsolvency Costs*, and *Insolvency Recovery Rate* are significantly associated with NPLs in recovery. Column (1) and (2) document that in expansionary periods an above median insolvency duration or above median insolvency costs are associated with NPL ratios that are on average approximately 7% higher compared to below median countries in recovery periods (p-value<0.02). In addition, I find that banks in countries with a high *Insolvency Recovery Rate* experience on average 6.6% lower NPL ratios relative to banks in countries with low recovery rates during economic recoveries.

I find corroborating results when looking at the three different contract enforcement measures. Table 3.5, Column (4)-(6) document that above median *Enforcement Duration* and *Enforcement Costs* are significantly positive associated with NPL ratios during economic upturns. Furthermore, banks in countries with overall better contract enforcement, and therefore, with a higher contract *Enforcement Score* experience on average 9% lower NPL ratios in economic upturns (p-value<0.01).

Overall, my results confirm the hypothesis that insolvency and contract enforcement procedures are significantly associated with NPLs on the country and on the bank level. Furthermore, I document that this association is confined to economic recovery periods.

Table 3.5 Contract enforcement, insolvency procedures and NPL ratios

	Insolvency Procedures			*Enforcement Procedures*		
NPL Ratio as Dependent Variable	*(1)* *Insolvency Duration*	*(2)* *Insolvency Costs*	*(3)* *Insolvency Recovery Rate*	*(4)* *Enforcement Duration*	*(5)* *Enforcement Costs*	*(6)* *Enforcement Score*
Test Variables:						
Split*Recovery	6.841**	7.288***	-6.645**	10.033***	7.149***	-9.010***
	(0.017)	(0.009)	(0.017)	(0.000)	(0.005)	(0.000)
Recovery	-4.491**	-4.519**	2.460**	-6.364***	-4.266**	3.399***
	(0.019)	(0.013)	(0.029)	(0.000)	(0.015)	(0.000)
GDP * Recovery	0.038	-0.011	0.013	0.173	0.009	0.140
	(0.851)	(0.955)	(0.950)	(0.236)	(0.962)	(0.413)
GDP	0.447***	0.377**	0.471***	0.083	0.394**	0.166*
	(0.008)	(0.018)	(0.007)	(0.491)	(0.038)	(0.093)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm	Year, Firm
SE Clustered by	Country	Country	Country	Country	Country	Country
N	13,664	13,664	13,664	13,664	13,664	13,664
R^2	0.252	0.259	0.251	0.318	0.263	0.292
Adj. R^2	0.251	0.258	0.250	0.317	0.262	0.291

Table 5 shows regression results for the effect of insolvency procedures, contract enforcement procedures, economic growth and bank-specific factors on the level of banks' non-performing loans ratio. *Insolvency Duration, Insolvency Costs, Insolvency Recovery Rate, Enforcement Duration, Enforcement Costs and Enforcement Score* are binary variables that take the value of '1' if the country is above the median for the respective split variable of all countries during the sample period from 2007-2016. Higher values for *Enforcement Score* indicate better contract enforcement procedures. *GDP* is the yearly GDP growth. *Recovery* is a binary variable that takes the value of '1' beginning in the first year that the country enters a period of three years consecutive GDP growth. All other variables are defined in Appendix D. We include year and firm fixed effects in the regressions, but do not report the coefficients. We winsorize all variables at the 1% and at the 99% level. The table reports OLS coefficient estimates and (in parentheses) *p-values* based on robust standard errors clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

3.4.5. Robustness tests

In the last step, I perform three robustness tests that replicate Table 4 with different sets of additional control variables. In Table 3.6, Column (1), I additionally interact all control variables with the binary *Recovery* variable to test whether the association between the bank-level control variables and NPLs changes over the business cycle. I confirm the inference from Table 3.4, although the coefficient on *High LE*Recovery* is slightly lower (6.58 vs. -6.6, p-value<0.05).

In the next step, I address concerns that NPL ratios that might also serve as a supervisory measure of financial stability are driven by supervisory power or general regulatory quality rather than legal efficiency. In Column (2), I employ additional controls for supervisory power, private monitoring, external governance and the requirement for external audit from Barth, Caprio, Levine (2013). My inference remains qualitatively and quantitatively robust. The main coefficient of interest *Legal Efficiency * Recovery* is significant at the 5% level although the effect size is slightly lower (-4.3 vs. -6.6, p-value<0.05). However, I do not document a significant association between the proxies for supervisory power and NPLs.

In Column (3), I alternatively employ additional control variables from the World Bank's Worldwide Governance Indicators (WGI) database to proxy for institutional differences and the strength of the legal system (Kaufmann, Kraay, and Mastruzzi, 2011). I proxy for six different constructs in this analysis: Political stability, voice and accountability, regulatory quality, rule of law, control of corruption and government effectiveness. I continue to find a significant negative association between *Legal Efficiency * Recovery* and the NPL ratio although the effect size is again slightly lower (-5.2 vs. -6.6, p-value<0.05).

Overall, I show that the incremental association between legal efficiency and NPLs in economic upturns remains robust even when controlling for proxies of supervisory power, overall regulatory quality and political stability. Future research can explore these additional covariates in more detail.

Table 3.6 Robustness tests with additional controls

Dependent Variable	(4) *NPL Ratio*	(4) *NPL Ratio*	(4) *NPL Ratio*
Test Variables:			
High LE	2.377	1.533	-0.245
	(0.139)	(0.417)	(0.839)
GDP	0.393**	0.495**	-0.209
	(0.022)	(0.011)	(0.137)
Recovery	4.443**	2.791***	1.502
	(0.048)	(0.006)	(0.259)
High LE * Recovery	-6.584**	-4.334**	-5.260**
	(0.013)	(0.036)	(0.015)
GDP * Recovery	-0.058	-0.124	0.400*
	(0.713)	(0.632)	(0.074)
Control Variables:			
Size	-0.301	-0.347	-0.860
	(0.494)	(0.492)	(0.162)
Loan Ratio	-0.822	-0.306**	-0.231***
	(0.175)	(0.018)	(0.000)
Cost-Income	-0.024***	-0.014***	-0.003
	(0.001)	(0.003)	(0.420)
Tier 1	-0.026	-0.044*	-0.038
	(0.102)	(0.060)	(0.126)
RoA	-0.624***	-0.502*	-0.433*
	-0.246	(0.090)	(0.079)
Constant	-0.301	-9.908	57.519***
	(0.494)	(0.186)	(0.001)
Additional Controls	Controls*Recovery	Bank Regulation and Supervision	Governance and Institutional Differences
Fixed Effects	Year, Firm	Year, Firm	Year, Firm
SE Clustered by	Country	Country	Country
Observations	14,151	14,151	14,151
R-squared	0.258	0.366	0.366
Adjusted R-squared	0.256	0.365	0.365

Table 3.6 replicates Table 4 using additional control variables for the general regulatory and legal environment, and supervisory power. Column (1) includes an interaction between Recovery and all control variables (*Size, Loan Ratio, Cost-Income, Tier 1, RoA*). Column (2) adds five different proxies for the regulatory and supervisory environment from Barth, Caprio, and Levine (2013): *Supervisory Power*, *Private Monitoring*, *External Audit*, and *External Governance*. Column (3) adds six different proxies for the general institutional environment from Kaufmann, Kraay, and Mastruzzi (2011): *Corruption, Government Effectiveness, Political Stability and Absence of Violence, Rule of Law, Regulatory Quality*, *Voice and Accountability*. *High LE* is a binary variable that takes the value of '1' if the country is above the median legal efficiency of all countries in that year. *GDP* is the yearly GDP growth. *Recovery* is a binary variable that takes the value of '1' beginning in the first year that the country enters a period of three years consecutive GDP growth. All other variables are defined in Appendix D. We include year and firm fixed effects in the regressions, but do not report the coefficients. We winsorize all variables at the 1% and at the 99% level. The table reports OLS coefficient estimates and (in parentheses) *p-values* based on robust standard errors clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

3.5. Conclusion

This paper has analyzed the determinants of NPLs from a new angle, one that explores the difference of macroeconomic, country-specific and bank-specific correlations with NPLs along the business cycle. Using country-level data on NPLs, I find that the time period from the start of an economic upturn until a reduction in NPLs occurs, is significantly shorter for countries with high legal efficiency. In addition, if insolvency and contract enforcement procedures are inefficient, this reduces the likelihood to get into a phase of decreasing NPLs even under favorable macroeconomic conditions.

I corroborate these findings with a bank-level analysis benchmarking differences in legal efficiency against other determinants of NPLs, such as GDP growth, regulatory capital, profitability, and cost efficiency. Similar to the evidence on the aggregate level, I find that banks in countries with high legal efficiency have on average incrementally lower NPLs during economic upturns. That is, my results suggest that the association of legal efficiency with NPLs changes over the business cycle. Further analyses reveal that these effects are robust for several proxies of legal efficiency. Furthermore, I provide evidence that the association of legal efficiency with NPLs is not confined to supervisory quality or the general regulatory quality within the country.

Finally, the findings can help to inform regulators, policymakers and supervisors when addressing high NPL levels in the future. This seems of particular relevance due to the recent pandemic-driven economic downturn that will likely result in NPL increases during the subsequent periods. However, my results back up the view that bank regulators and supervisors may only have parts of the toolkit that is needed to foster a swift NPL resolution process after economic downturns.

3.6. Appendix D: Variable definitions

Variable	Definition / Description	Data Source
Firm-level Variables		
TIER 1	(Tier 1 capital / total risk-weighted assets)*100	Capital IQ MI
Size	Ln(total assets)	Capital IQ MI
Loan Ratio	Total gross loans/ total assets	Capital IQ MI
Cost-Income	(Operating expenses / operating income)*100	Capital IQ MI
RoA	(Pre-provision net income / total assets)*100	Capital IQ MI
NPL Ratio	(Non-performing loans / total gross loans)*100	Capital IQ MI
Country Variables		
GDP	Yearly % growth in gross domestic product	World Bank
NPL Ratio	(Non-performing loans / total gross loans)*100	World Bank
Legal Efficiency (LE)	Summary Measure: Number of measures for which a country is below the median of all sample countries: Insolvency duration. Enforcement duration, insolvency cost, enforcement costs, insolvency recovery rate.	Djankov et al. (2003); Djankov et al., (2008)
Insolvency Duration	Above Median Average Duration for Insolvency Procedures	Djankov et al., (2008)
Enforcement. Duration	Above Median Average Days for Contract Enforcement Procedures	Djankov et al. (2003)
Insolvency Costs	Above Median Average Costs for Insolvency Procedures	Djankov et al., (2008)
Enforcement Costs	Above Median Average Costs for Contract Enforcement Procedures	Djankov et al. (2003)
Insolvency. Rec. Rate	Above Median Recovery Rate in Insolvencies	Djankov et al., (2008)
Enforcement. Score	Above Median Contract Enforcement Score	Djankov et al. (2003)
Supervisory Power	Whether the supervisory authorities have the authority to take specific actions to prevent and correct problems	Barth, Caprio, and Levine (2013)
Private Monitoring	Measures whether there incentives/ability for the private monitoring of firms, with higher values indicating more private monitoring	Barth, Caprio, and Levine (2013)
External Audit	The effectiveness of external audits of banks	Barth, Caprio, and Levine (2013)
External Governance	Higher values indicate better corporate governance (audit, accounting, financial statement transparency, external ratings and credit monitoring)	Barth, Caprio, and Levine (2013)
Corruption	Control of corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.	Kaufmann, Kraay, and Mastruzzi (2011)
Government Effectiveness	Government effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.	Kaufmann, Kraay, and Mastruzzi (2011)
Political Stability and Absence of Violence	Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism.	Kaufmann, Kraay, and Mastruzzi (2011)

3.6 Appendix D (continued)

Variable	Definition / Description	Data Source
Rule of Law	Rule of law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.	Kaufmann, Kraay, and Mastruzzi (2011)
Regulatory Quality	Regulatory quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.	Kaufmann, Kraay, and Mastruzzi (2011)
Voice and Accountability	Voice and accountability captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.	Kaufmann, Kraay, and Mastruzzi (2011)

Concluding Remarks

This thesis presents three essays on financial reporting incentives and bank transparency. While the first study documents the importance of manager incentives and preferences for banks' accounting choices, the second and the third study explore firm- and country-specific incentives that matter for banks' accounting and reporting behavior.

Chapter 1 investigates the role of individual managers in the financial reporting of banks. Exploiting the connectedness between different managers as well as a set of plausibly exogenous manager turnovers, we find that managerial idiosyncrasies explain approximately 19% of banks' discretionary loan loss provisions. We identify common patterns in bank managers' reporting behavior over time that point at general differences in the idiosyncratic influence across managers. Using these differences to construct bank manager profiles, we document how the role of individual manager types interacts with top management team composition. Overall, divergence in the revealed preferences of the top management team for different accounting and policy choices significantly confines the idiosyncratic manager influence on banks' loan loss provisioning

Chapter 2 investigates how supervisors influence bank transparency through supervisory disclosures and public enforcement. Upon adoption of the Single Supervisory Mechanism (SSM) for major Eurozone banks, the European Central Bank (ECB) as the new supervisor undertook a comprehensive review of bank balance sheets and publicly disclosed the results of this Asset Quality Review (AQR). The AQR disclosures revealed what the ECB perceived to be a substantial overvaluation of bank assets, and in particular problem loans. The magnitude of the AQR adjustments varied substantially across supervised banks. We exploit this firm-level variation as well as the staggered introduction of the SSM to analyze the change in affected banks' reporting behavior and transparency. The ECB's preference for more conservative reporting is associated with higher levels of loan loss provisions and non-performing loan classifications in the following periods. Pointing at the role of enforcement institutions, this reporting effect is particularly pronounced for firms whose prior national supervisors were more likely to be captured by political interest. At the same time, corresponding positive liquidity effects are concentrated among SSM banks that were exposed to potential pressure from market forces. Our findings suggest that supervisory disclosures are potentially effective in establishing greater transparency of the banking sector, but depend on the presence of firm-level incentives that help establish market discipline.

Finally, in Chapter 3, I investigate the role of legal efficiency for banks' non-performing loans along the business cycle in 17 European countries. During the global financial crisis and the subsequent sovereign debt crisis all European countries experienced a substantial increase in NPLs. I find that increases in NPLs are mainly associated with macroeconomic and bank-specific determinants. However, I recognize that substantial differences in the duration and efficiency of the NPL resolution after the crisis exist. I exploit cross-country differences in insolvency and contract enforcement procedures to document that non-performing loans are associated with the duration and the costs of insolvency and contract enforcement during economic growth phases. My findings suggest that the duration of the decreasing NPL phase depends on the presence of an efficient insolvency and contract enforcement regime that ensures swift non-performing loan resolution while the duration of increasing NPL phases is mainly determined by economic conditions.

References

Abowd, J. M., Kramarz, F., Margolis, D. N., Abowd, B. Y. J. M., Kramarz, F., & Margolis, D. N. (1999). High Wage Workers and High Wage Firms, *Econometrica, 67*(2), 251-333.

Abowd, J. M., Creecy, R. H., & Kramarz, F. (2002). Computing person and firm effects using linked longitudinal employer-employee data, *Center for Economic Studies*, (No. 2002-06), US Census Bureau.

Acharya, V. V., & Ryan, S. G. (2016). Banks' financial reporting and financial system stability. *Journal of Accounting Research*, 54(2), 277-340.

Acharya, V. V., & Steffen, S. (2014). Making sense of the comprehensive assessment. SAFE Policy Letter, Research Report No. 32. Retrieved from https://www.econstor.eu/handle/10419/106982

Adams, R., & Ferreira, D. (2010). Moderation in groups: Evidence from betting on ice break-ups in Alaska. *The Review of Economic Studies*, 77(3), 882-913.

Adams, R., Keloharju, M., & Knüpfer, S. (2018). Are CEOs born leaders? Lessons from traits of a million individuals. *Journal of Financial Economics*, 130(2), 392-408.

Agarwal, S., Amromin, G., Ben-David, I., & Dinc, S. (2018). The Politics of Foreclosures. *The Journal of Finance*, 73(6), 2677-2717.

Agarwal, S., Lucca, D., Seru, A., & Trebbi, F. (2014). Inconsistent regulators: Evidence from banking. *The Quarterly Journal of Economics*, 129(2), 889-938.

Agoraki, M. E. K., Delis, M. D., & Pasiouras, F. (2011). Regulations, competition and bank risk-taking in transition countries. *Journal of Financial Stability*, 7(1), 38-48.

Ahmed, A. S., Takeda, C., & Thomas, S. (1999). Bank loan loss provisions: a reexamination of capital management, earnings management and signaling effects. *Journal of Accounting and Economics*, *28*(1), 1-25.

Ahmed, A. S., Christensen, B. E., Olson, A. J., & Yust, C. G. (2019). Déjà vu: The effect of executives and directors with prior banking crisis experience on bank outcomes around the global financial crisis. *Contemporary Accounting Research*, 36(2), 958-998.

Albuquerque, A. M., De Franco, G., & Verdi, R. S. (2013). Peer choice in CEO compensation. *Journal of Financial Economics*, 108(1), 160-181.

Ali, A., & Zhang, W. (2015). CEO tenure and earnings management. *Journal of Accounting and Economics*, 59(1), 60-79.

Andrews, M. J., Gill, L., Schank, T., & Upward, R. (2008). High wage workers and low wage firms: negative assortative matching or limited mobility bias? *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *171*(3), 673-697.

Angrist, J. D., & Pischke, J. S. (2008). Mostly harmless econometrics: An empiricist's companion. NJ: Princeton University Press.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), 29-51.

Armstrong, C. S., Guay, W. R., & Weber, J. P. (2010). The role of information and financial reporting in corporate governance and debt contracting. *Journal of Accounting and Economics*, 50(2-3), 179-234.

Armstrong, C. S., Larcker, D. F., Ormazabal, G., & Taylor, D. J. (2013). The relation between equity incentives and misreporting: The role of risk-taking incentives. *Journal of Financial Economics*, 109(2), 327-350.

Baik, B. O. K., Farber, D. B., & Lee, S. A. M. (2011). CEO ability and management earnings forecasts. *Contemporary Accounting Research*, 28(5), 1645-1668.

Bamber, L. S., Jiang, J., & Wang, I. Y. (2010). What's my style? The influence of top managers on voluntary corporate financial disclosure. *The Accounting Review*, *85*(4), 1131-1162.

Bantel, K. A., & Jackson, S. E. (1989). Top management and innovations in banking: Does the composition of the top team make a difference? *Strategic Management Journal*, 10(S1), 107-124.

Barseghyan, L. (2010). Non-performing loans, prospective bailouts, and Japan's slowdown. *Journal of Monetary Economics*, 57(7), 873-890.

Barth, J. R., Caprio Jr, G., & Levine, R. (2004). Bank regulation and supervision: what works best? *Journal of Financial Intermediation*, 13, 205-248.

Barth, J. R., Caprio, G., & Levine, R. (2013). Bank regulation and supervision in 180 countries from 1999 to 2011. *Journal of Financial Economic Policy*. 5(2), 111-219.

Barth, M. E., & Landsman, W. R. (2010). How did financial reporting contribute to the financial crisis?. *European Accounting Review*, 19(3), 399-423.

Beatty, A. L., Ke, B., & Petroni, K. R. (2002). Earnings management to avoid earnings declines across publicly and privately held banks. *The Accounting Review*, 77(3), 547-570.

Beatty, A., & Liao, S. (2014). Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics*, *58*(2-3), 339-383.

Beaver, W., Eger, C., Ryan, S., & Wolfson, M. (1989). Financial reporting, supplemental disclosures, and bank share prices. *Journal of Accounting Research*, 27(2), 157-178.

Behr, P., Schmidt, R. H., & Xie, R. (2010). Market structure, capital regulation and bank risk taking. *Journal of Financial Services Research*, 37(2-3), 131-158.

Berger, A. N., & De Young, R. (1997). Problem loans and cost efficiency in commercial banking. *Journal of Banking & Finance*, 21, 849-870.

Beck, R., Jakubik, P., & Piloiu, A. (2013). Non-performing loans: What matters in addition to the economic cycle? Working Paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2214971

Beck, P.J. & Narayanamoorthy, G.S., (2013). Did the SEC impact banks' loan loss reserve policies and their informativeness? *Journal of Accounting and Economics*, 56(2-3), pp.42-65.

Beltratti, A., & Stulz, R. M. (2012). The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics*, 105(1), 1-17.

Berger, A. N., Kick, T., & Schaeck, K. (2014). Executive board composition and bank risk taking. *Journal of Corporate Finance*, 28, 48-65.

Berger, A. N., Davies, S. M., & Flannery, M. J. (2000). Comparing market and supervisory assessments of bank performance: who knows what when? *Journal of Money, Credit and Banking*, 32(3), 641-667.

Berger, A. N., & Turk-Ariss, R. (2015). Do Depositors Discipline Banks and Did Government Actions During the Recent Crisis Reduce this Discipline? An International Perspective. *Journal of Financial Services Research*, 48(2), 103-126.

Bertrand, M., & Schoar, A. (2003). Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics*, 118(4), 1169-1208.

Bhat, G., Ryan, S. G., & Vyas, D. (2018). The Implications of Credit Risk Modeling for Banks' Loan Loss Provisions and Loan-Origination Procyclicality. *Management Science*, 65(5), 2116-2141.

Bischof, J., & Daske, H. (2013). Mandatory Disclosure, Voluntary Disclosure, and Stock Market Liquidity: Evidence from the EU Bank Stress Tests. *Journal of Accounting Research*, 51(5), 997-1029.

Bischof, J., Daske, H., Elfers, F., & Hail, L. (2020). A tale of two supervisors: Compliance with risk disclosure regulation in the banking sector. Working Paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2580569

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115-143.

Bofondi, M., & Ropele, T. (2011). Macroeconomic determinants of bad loans: evidence from Italian banks. Bank of Italy Occasional Paper, (89). Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1849872

Breuer, J. B. (2006). Problem bank loans, conflicts of interest, and institutions. *Journal of Financial Stability*, 2(3), 266-285.

Brochet, F., Miller, G. S., Naranjo, P., & Yu, G. (2019). Managers' cultural background and disclosure attributes. *The Accounting Review*, 94(3), 57-86.

Busch, D., & Teubner, A. (2019). Fit and Proper Assessments within the Single Supervisory Mechanism. European Banking Institute Working Paper Series 2019, No. 34, Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3346976

Bushman, R. M. (2014). Thoughts on financial accounting and the banking industry. *Journal of Accounting and Economics*, 58(2-3), 384-395.

Bushman, R. M., & Williams, C. D. (2012). Accounting discretion, loan loss provisioning, and discipline of Banks' risk-taking. *Journal of Accounting and Economics*, 54(1), 1-18.

Bushman, R. M., & Williams, C. D. (2015). Delayed expected loss recognition and the risk profile of banks. *Journal of Accounting Research*, 53(3), 511-553.

Bushman, R. M. (2016). Transparency, accounting discretion, and bank stability. *Economic Policy Review*, August, 129-149.

Bushman, R. M., Davidson, R. H., Dey, A., & Smith, A. (2018). Bank CEO materialism: Risk controls, culture and tail risk. *Journal of Accounting and Economics*, 65(1), 191-220

Busuioc, E. M. (2016). Friend or foe? Inter-agency cooperation, organizational reputation, and turf. *Public Administration*, 94(1), 40-56.

Caliński, T., & Harabasz, J. (1974). A dendrite method for cluster analysis. *Communications in Statistics-Theory and Methods*, 3(1), 1-27.

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

Campbell, T. C., Gallmeyer, M., Johnson, S. A., Rutherford, J., & Stanley, B. W. (2011). CEO optimism and forced turnover. *Journal of Financial Economics*, *101*(3), 695-712.

Carboni, M., Fiordelisi, F., Ricci, O., & Lopes, F. S. S. (2017). Surprised or not surprised? The investors' reaction to the comprehensive assessment preceding the launch of the banking union. *Journal of Banking & Finance*, 74(Supplement C), 122-132.

Cerulli,G., D'Apice, V., Fiordelisi, F., Masala, F. (2019). Benchmarking Non-Performing Loans. Working Paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2903851

Chapman, K. L., Miller, G. S., & White, H. D. (2019). Investor relations and information assimilation. *The Accounting Review*, 94(2), 105-131.

Chen, Y., & Hasan, I. (2006). The transparency of the banking system and the efficiency of information-based bank runs. *Journal of Financial Intermediation*, 15(3), 307-331.

Choi, W., Han, S., Jung, S. H., & Kang, T. (2015). CEO's operating ability and the association between accruals and future cash flows. *Journal of Business Finance & Accounting*, 42(5-6), 619-634.

Christensen, D. M., Jones, K. L., & Kenchington, D. G. (2018). Gambling attitudes and financial misreporting. *Contemporary Accounting Research*, 35(3), 1229-1261.

Christensen, H. B., Hail, L., & Leuz, C. (2013). Mandatory IFRS reporting and changes in enforcement. *Journal of Accounting and Economics*, 56(2-3), 147-177.

Christensen, H. B., Maffett, M., & Vollon, L. (2019). Securities regulation, household equity ownership, and trust in the stock market. *Review of Accounting Studies*, 24(3), 824-859.

Coles, J. L., Daniel, N. D., & Naveen, L. (2006). Managerial incentives and risk-taking. *Journal of Financial Economics*, 79(2), 431-468.

Collins, J. H., Shackelford, D. A., & Wahlen, J. M. (1995). Bank differences in the coordination of regulatory capital, earnings, and taxes. *Journal of Accounting Research*, 33(2), 263-291.

Core, J., & Guay, W. (2002). Estimating the value of employee stock option portfolios and their sensitivities to price and volatility. *Journal of Accounting Research*, 40(3), 613-630.

Costello, A. M., Granja, J., & Weber, J. (2019). Do Strict Regulators Increase the Transparency of Banks? *Journal of Accounting Research*, 57(3), 603-637.

Crossland, C., & Hambrick, D. C. (2007). How national systems differ in their constraints on corporate executives: A study of CEO effects in three countries. *Strategic Management Journal*, 28(8), 767-789.

Curry, T.J. (2013). Remarks before the AICPA Banking Conference, September 16, 2013. Retrieved from https://www.occ.treas.gov/news-issuances/speeches/2013/pub-speech-2013-136.pdf

Custodio, C., & Metzger, D. (2014). Financial expert CEOs: CEO′ s work experience and firm′ s financial policies. *Journal of Financial Economics*, 114(1), 125-154.

D'Apice, V., & Fiordelisi, F. (2020). Judicial Efficiency and Lending Quality. Working Paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3557159

Davidson, R., Dey, A., & Smith, A. (2015). Executives' "off-the-job" behavior, corporate culture, and financial reporting risk. *Journal of Financial Economics*, *117*(1), 5-28.

Davidson, R. H., Dey, A., & Smith, A. J. (2019). CEO materialism and corporate social responsibility. *The Accounting Review*, 94(1), 101-126.

Davis, A. K., Ge, W., Matsumoto, D., & Zhang, J. L. (2015). The effect of manager-specific optimism on the tone of earnings conference calls. *Review of Accounting Studies*, *20*(2), 639-673.

Dejong, D., & Ling, Z. (2013). Managers: Their effects on accruals and firm policies. *Journal of Business Finance & Accounting*, 40(1-2), 82-114.

Demerjian, P. R., Lev, B., Lewis, M. F., & McVay, S. E. (2013). Managerial ability and earnings quality. *Accounting Review*, *88*(2), 463-498.

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

Dessein, W., & Santos, T. (2020) Managerial Style and Attention. *American Economic Journal: Microeconomics*, forthcoming.

Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. The *Journal of Finance*, 46(4), 1325-1359.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147-160.

Dimitrios, A., Helen, L., & Mike, T. (2016). Determinants of non-performing loans: Evidence from Euro-area countries. *Finance Research Letters*, 18, 116-119.

Djankov, S., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2003). Courts. *The Quarterly Journal of Economics*, 118(2), 453-517.

Djankov, S., Hart, O., McLiesh, C., & Shleifer, A. (2008). Debt enforcement around the world. *Journal of Political Economy*, 116(6), 1105-1149.

Dudley, W. (2009). Some lessons from the crisis. Remarks at the Institute of International Banks Membership Luncheon, New York City.

Dugan, J. C (2009). Loan Loss Provisioning and Pro-cyclicality. Remarks before the Institute of International Bankers, March 2, 2009. Retrieved from https://www.occ.gov/news-issuances/speeches/2009/pub-speech-2009-16.pdf

Duro, M., Heese, J., & Ormazabal, G. (2019). The effect of enforcement transparency: Evidence from SEC comment-letter reviews. *Review of Accounting Studies*, 24(3), 780-823.

Dyreng, S. D., Hanlon, M., & Maydew, E. L. (2010). The effects of executives on corporate tax avoidance. *Accounting Review*, *85*(4), 1163-1189.

Dyreng, S. D., Mayew, W. J., & Williams, C. D. (2012). Religious social norms and corporate financial reporting. *Journal of Business Finance & Accounting*, 39(7-8), 845-875.

Eber, M., & Minoiu, C. (2017). How Do Banks Adjust to Stricter Supervision? Working Paper. Retrieved from https://papers.ssrn.com/abstract=2662502

EC (2014). Eurobarometer Survey. European Commission. Retrieved from https://ec.europa.eu/commfrontoffice/publicopinion/index.cfm

ECB (2014a). Guide to banking supervision. European Central Bank, November 2014. Retrieved from https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssmguidebankingsupervision201411.en.pdf?807838fa2-a8bb958749f411c432d1f3e

ECB (2014b). Aggregate Report on the Comprehensive Assessment. European Central Bank, October 2014. Retrieved from https://www.bankingsupervision.europa.eu/ecb/pub/pdf/aggregatereportonthecomprehensiveassessmentexsum201410.en.pdf?7e232769b9508e18b653e6dffa1b1f8e

ECB (2016). Stocktake of national supervisory practices and legal frameworks related to NPLs. European Central Bank. Retrieved from https://www.bankingsupervision.europa.eu/legalframework/publiccons/pdf/npl/stock_taking.en.pdf

ECB (2017). Stocktake of national supervisory practices and legal frameworks related to NPLs. European Central Bank. Retrieved from https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.stock_taking2017.en.pdf

ECB (2018a). Guide to fit and proper assessments. Retrieved from https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.fap_guide_201705_rev_201805.en.pdf

ECB (2018b). SSM Supervisory Manual - European banking supervision: functioning of the SSM and supervisory approach. European Central Bank, March 2018. Retrieved from https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.supervisorymanual201803.en.pdf?1584b27046baf-1e68f92f82caadb3a63

ECB (2019). Communication on supervisory coverage expectations for NPEs. European Central Bank. Retrieved from https://www.bankingsupervision.europa.eu/press/letterstobanks/shared/pdf/2019/ssm.supervisory_coverage_expectations_for_NPEs_201908.en.pdf

ECOFIN (2017). Non-Performing Loans – Action Plan. European Commission: Council Economic and Financial Affairs. 3555th Council meeting, Brussels.

Edmans, A., Gabaix, X., & Landier, A. (2009). A multiplicative model of optimal CEO incentives in market equilibrium. *The Review of Financial Studies*, 22(12), 4881-4917.

Espinoza, R., Prasad, A., & Williams, O. (2011). Regional financial integration in the GCC. *Emerging Markets Review*, 12(4), 354-370.

European Court of Auditors (2016). Single Supervisory Mechanism - Good Start, but Further Improvement Needed. Special Report 29/2016. Retrieved from https://www.eca.europa.eu/en/Pages/DocItem.aspx?did=39744

Fee, C. E., Hadlock, C. J., & Pierce, J. R. (2013). Managers with and without style: Evidence using exogenous variation. *The Review of Financial Studies*, 26(3), 567-601.

Fernandes, M., Igan, D., & Pinheiro, M. (2017). March madness in Wall Street: (What) does the market learn from stress tests? *Journal of Banking & Finance*, 112, 105250.

Ferri, F., Zheng, R., & Zou, Y. (2018). Uncertainty about managers' reporting objectives and investors' response to earnings reports: Evidence from the 2006 executive compensation disclosures. *Journal of Accounting and Economics*, 66(2-3), 339-365.

Filip, B. F. (2014). Non-performing loans-dimension of the non-quality of bank lending/loans and their specific connections. *Theoretical and Applied Economics*, 5(594), 127-146.

Financial Times (2009). Fortis shareholders leave Belgian depositors out cold. Financial Times, February 12, 2009. Retrieved from https://www.ft.com/content/3926631c-f93e-11dd-90c1-000077b07658

Financial Times (2010).UK and US call for bank transparency. Financial Times, June 3, 2010. Retrieved from https://www.ft.com/content/a3122ce0-6ea2-11df-ad16-00144feabdc0

Financial Times (2011). Dexia agrees to Belgian bail-out. Financial Times, October 10, 2011. Retrieved from https://www.ft.com/content/af0f7f4e-f307-11e0-8383-00144feab49a

Financial Times (2017). Nordea to move its headquarters to Finland. Financial Times, September 6, 2017. Retrieved from https://www.ft.com/content/1ed979fe-9318-11e7-a9e6-11d2f0ebb7f0

Fiordelisi, F., Ricci, O., & Lopes, F. S. S. (2017). The Unintended Consequences of the Launch of the Single Supervisory Mechanism in Europe. *Journal of Financial and Quantitative Analysis*, 52(6), 2809-2836.

Fitch (2019). Basel Foreclosure Proposal May Push EU Insolvency Reform. Retrieved from https://www.reuters.com/article/idUSFit953307

Flannery, M. J. (1994) Debt maturity and the deadweight cost of leverage: optimally financing banking firms. *American Economic Review*, 84, 320-331.

Flannery, M. J. (2001). The Faces of "Market Discipline". *Journal of Financial Services Research*, 20(2-3), 107-119.

Flannery, M., Hirtle, B., & Kovner, A. (2017). Evaluating the information in the federal reserve stress tests. *Journal of Financial Intermediation*, 29, 1-18.

Freixas, X., & Laux, C. (2011). Disclosure, transparency, and market discipline. Working Paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1964321

Fremeth, A. R., & Holburn, G. L. F. (2012). Information Asymmetries and Regulatory Decision Costs: An Analysis of U.S. Electric Utility Rate Changes 1980-2000. *Journal of Law, Economics, and Organization*, 28(1), 127-162.

Gallemore, J. (2019). Bank Financial Reporting Opacity and Regulatory Intervention. Working Paper. Retrieved from https://ssrn.com/abstract=2838541

Garlappi, L., Giammarino, R., & Lazrak, A. (2017). Ambiguity and the corporation: Group disagreement and underinvestment. *Journal of Financial Economics*, *125*(3), 417-433.

Ge, W., Matsumoto, D., & Zhang, J. L. (2011). Do CFOs have style? An empirical investigation of the effect of individual CFOs on accounting practices. *Contemporary Accounting Research*, 28(4), 1141-1179.

Gebhardt, G. U., & Novotny-Farkas, Z. (2011). Mandatory IFRS Adoption and Accounting Quality of European Banks. *Journal of Business Finance & Accounting*, 38(3-4), 289-333.

Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, 20, 93-104.

Ghosh, S. (2007). Does Financial Liberalization Lower Problem Loans in Banks? *Economic Notes*, 36(2), 171-188.

Gipper, B., Leuz, C., & Maffett, M. (2019). Public Oversight and Reporting Credibility: Evidence from the PCAOB Audit Inspection Regime. *The Review of Financial Studies*, forthcoming.

Goldstein, I., & Sapra, H. (2014). Should banks' stress test results be disclosed? An analysis of the costs and benefits. *Foundations and Trends in Finance*, 8(1), 1-54.

Goldstein, I., & Yang, L. (2019). Good disclosure, bad disclosure. *Journal of Financial Economics*, 131(1), 118-138.

Gormley, T. A., & Matsa, D. A. (2014). Common errors: How to (and not to) control for unobserved heterogeneity. *The Review of Financial Studies*, 27(2), 617-661.

Graham, J. R., Li, S., & Qiu, J. (2012). Managerial attributes and executive compensation. *Review of Financial Studies*, *25*(1), 144-186.

Graham, J. R., Harvey, C. R., & Puri, M. (2013). Managerial attitudes and corporate actions. *Journal of Financial Economics*, 109(1), 103-121.

Granja, J. (2018). Disclosure regulation in the commercial banking industry: Lessons from the national banking era. *Journal of Accounting Research*, 56(1), 173-216.

Granja, J., & Leuz, C. (2019). The Death of a Regulator: Strict Supervision, Bank Lending and Business Activity Retrieved from https://papers.ssrn.com/abstract=3092284

Griffin, P. A., & Wallach, S. J. (1991). Latin American lending by major US banks: The effects of disclosures about nonaccrual loans and loan loss provisions. *Accounting Review*, 66(4), 830-846.

Gropp, R., Mosk, T., Ongena, S., & Wix, C. (2019). Banks response to higher capital requirements: Evidence from a quasi-natural experiment. *The Review of Financial Studies*, 32(1), 266-299.

Guryan, J. (2001). Does money matter? Regression-discontinuity estimates from education finance reform in Massachusetts (No. w8269). *National Bureau of Economic Research*.

Hagendorff, J., Collins, M., & Keasey, K. (2010). Board monitoring, regulation, and performance in the banking industry: Evidence from the market for corporate control. *Corporate Governance: An International Review*, 18(5), 381-395.

Hagendorff, J., Saunders, A., Steffen, S., & Vallascas, F. (2018). The Wolves of Wall Street : Managerial Attributes and Bank Business Models. Working Paper, Retrieved from https://papers.ssrn.com/Sol3/papers.cfm?abstract_id=2670525

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, 20(1), 25-46.

Ham, C., Seybert, N., & Wang, S. (2018). Narcissism is a bad sign: CEO signature size, investment, and performance. *Review of Accounting Studies*, 23(1), 234-264.

Hambrick, D. C., & Mason, P. A. (1984). Upper Echelons: The Organization as a Reflection of Its Top Managers. *Academy of Management Review*, *9*(2), 193-206.

Hambrick, D. C. (2007). Upper echelons theory: An update. *Academy of Management Review*, 32(2), 334-343.

Hambrick, D. C., & Quigley, T. J. (2014). Toward more accurate contextualization of the CEO effect on firm performance. *Strategic Management Journal*, 35(4), 473-491.

Haselmann, R., Pistor, K., & Vig, V. (2010). How law affects lending. *The Review of Financial Studies*, 23(2), 549-580.

Herring, R., (2004). How can the invisible hand strengthen prudential supervision? And how can prudential supervision strengthen the invisible hand? in: Borio, C. et al. (ed.), Market Discipline Across Countries and Industries, MIT Press, Cambridge, MA.

Hollander, S., & Verriest, A. (2016). Bridging the gap: the design of bank loan contracts and distance. *Journal of Financial Economics*, 119(2), 399-419.

Holthausen, R. W. (2009). Accounting Standards, Financial Reporting Outcomes, and Enforcement. *Journal of Accounting Research*, 47(2), 447-458.

Homar, T., Kick, H., & Salleo, C. (2015). What Drives Forbearance-Evidence from the ECB Comprehensive Assessment. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2707565

Hoshi, T., & Kashyap, A. K. (2010). Will the US bank recapitalization succeed? Eight lessons from Japan. *Journal of Financial Economics*, 97(3), 398-417.

Hribar, P., & Yang, H. (2016). CEO overconfidence and management forecasting. *Contemporary Accounting Research*, 33(1), 204-227.

Huang, H. W., Rose-Green, E., & Lee, C. C. (2012). CEO age and financial reporting quality. *Accounting Horizons*, 26(4), 725-740.

Huang, J., & Kisgen, D. J. (2013). Gender and corporate finance: Are male executives overconfident relative to female executives? *Journal of Financial Economics*, 108(3), 822-839.

IMF (2015). A Strategy for Resolving Europe's Problem Loans. IMF Staff Discussion Note SDN/15/19. Retrieved from https://www.imf.org/external/pubs/ft/sdn/2015/sdn1519.pdf

IMF (2018). Euro Area Policies: Financial System Stability Assessment. IMF Staff Country Report No. 18/226. Retrieved from https://www.imf.org/en/Publications/CR/Issues/2018/07/19/Euro-Area-Policies-Financial-System-Stability-Assessment-46100

Jackson, H. E., & Roe, M. J. (2009). Public and private enforcement of securities laws: Resource-based evidence. *Journal of Financial Economics*, 93(2), 207-238.

Jappelli, T., Pagano, M., & Bianco, M. (2005). Courts and banks: Effects of judicial enforcement on credit markets. *Journal of Money, Credit and Banking*, 223-244.

Jia, Y., Lent, L. Van, & Zeng, Y. (2014). Masculinity, testosterone, and financial misreporting. *Journal of Accounting Research*, *52*(5), 1195-1246.

Jiang, L., Levine, R., & Lin, C. (2016). Competition and Bank Opacity. *Review of Financial Studies*, *29*(7), 1911-1942.

Jiang (Xuefeng), J., Petroni, K.R. & Yanyan Wang, I., (2010). CFOs and CEOs: Who have the most influence on earnings management? *Journal of Financial Economics*, 96(3), pp.513-526.

Kanagaretnam, K., Lobo, G. J., & Yang, D. H. (2004). Joint tests of signaling and income smoothing through bank loan loss provisions. *Contemporary Accounting Research*, 21(4), 843-884.

Karagianni, A., & Scholten, M. (2018). Accountability Gaps in the Single Supervisory Mechanism (SSM) Framework. *Utrecht Journal of International & European Law*, 34(2), 185-194.

Kauko, K. (2012). External deficits and non-performing loans in the recent financial crisis. *Economics Letters*, 115(2), 196-199.

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2011). The worldwide governance indicators: methodology and analytical issues. *Hague Journal on the Rule of Law*, 3(2), 220-246.

Klein, N. (2013). Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance. IMF Working Paper, WP/13/72. Retrieved from https://www.imf.org/~/media/Websites/IMF/imported-full-text-pdf/external/pubs/ft/wp/2013/_wp1372.ashx

Kleymenova, A. & Tomy, R. (2020) Regulators' Disclosure Decisions: Evidence from Bank Enforcement Actions. Working Paper. Retrieved from https://ssrn.com/abstract=3327502.

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

Lambert, T. (2018). Lobbying on regulatory enforcement actions: Evidence from US commercial and savings banks. *Management Science*, 65(6), 2445-294.

LaPorta, R., Lopez-de-Silanes, F, & Shleifer, A. (2006). What Works in Securities Laws? *Journal of Finance*, 61(1), 1-32.

Lauck, J., Rakestraw, J., & Stein, S. E. (2020). Do Audit Fees Reflect Unique Characteristics of Individual Executives? Working Paper, available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2639777

Law, K. K., & Mills, L. F. (2017). Military experience and corporate tax avoidance. *Review of Accounting Studies*, 22(1), 141-184.

Lazzari, V., Vena, L., & Venegoni, A. (2017). Stress tests and asset quality reviews of banks: A policy announcement tool. *Journal of Financial Stability*, 32(Supplement C), 86-98.

Leuz, C., & R. Verrecchia, 2000, The economic consequences of increased disclosure. *Journal of Accounting Research*, 38(Supplement: Studies on Accounting Information and the Economics of the Firm), 91-124.

Leuz, C., & Wysocki, P. D. (2016). The Economics of Disclosure and Financial Reporting Regulation: Evidence and Suggestions for Future Research. *Journal of Accounting Research*, 54(2), 525-622.

Li, N., & Wahid, A. S. (2018). Director tenure diversity and board monitoring effectiveness. *Contemporary Accounting Research*, 35(3), 1363-1394.

Liu, T., Mao, Y., & Tian, X. (2017). The role of human capital: Evidence from patent generation. Working Paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2728924

Liu, C. C., & Ryan, S. G. (2006). Income smoothing over the business cycle: Changes in banks' coordinated management of provisions for loan losses and loan charge-offs from the pre-1990 bust to the 1990s boom. *The Accounting Review*, *81*(2), 421-441.

Livne, G., Markarian, G., & Milne, A. (2011). Bankers' compensation and fair value accounting. *Journal of Corporate Finance*, *17*(4), 1096-1115.

Loipersberger, F. (2018). The Effect of Supranational Banking Supervision on the Financial Sector: Event Study Evidence from Europe. *Journal of Banking & Finance*, 91, 34-48.

Lopes de Melo, R. (2018). Firm wage differentials and labor market sorting: Reconciling theory and evidence. *Journal of Political Economy*, 126(1), 313-346.

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance*, 36(4), 1012-1027.

Macey, J. R., & O'Hara, M. (2016). Bank corporate governance: a proposal for the post-crisis world. *Economic Policy Review*, Issue Aug, 85-105.

Macher, J. T., & Mayo, J. W. (2012). The World of Regulatory Influence. *Journal of Regulatory Economics*, 41(1), 59-79.

Macher, J. T., Mayo, J. W., & Nickerson, J. A. (2011). Regulator Heterogeneity and Endogenous Efforts to Close the Information Asymmetry Gap. *The Journal of Law and Economics*, 54(1), 25-54.

Maechler, A. M., & McDill, K. M. (2006). Dynamic depositor discipline in US banks. *Journal of Banking & Finance*, 30(7), 1871-1898.

Maennasoo, K., & Mayes, D. G. (2009). Explaining bank distress in Eastern European transition economies. *Journal of Banking & Finance*, 33(2), 244-253.

Malmendier, U., Tate, G., & Yan, J. (2011). Overconfidence and early-life experiences: the effect of managerial traits on corporate financial policies. *The Journal of Finance*, 66(5), 1687-1733.

Mamatzakis, E., Matousek, R., & Vu, A. N. (2016). What is the impact of bankrupt and restructured loans on Japanese bank efficiency? *Journal of Banking & Finance*, 72(Supplement), 187-202.

Meyer, B. D. (1990). Unemployment Insurance and Unemployment Spells. *Econometrica*, 58(4), 757-782.

Morgan, D. P., Peristiani, S., & Savino, V. (2014). The Information Value of the Stress Test. *Journal of Money, Credit and Banking*, 46(7), 1479-1500.

Morrison, A. D., & White, L. (2013). Reputational contagion and optimal regulatory forbearance. *Journal of Financial Economics*, 110(3), 642-658.

Nguyen, D. D., Hagendorff, J., & Eshraghi, A. (2017). Does a CEO's cultural heritage affect performance under competitive pressure? *The Review of Financial Studies*, 31(1), 97-141.

Nichols, D. C., Wahlen, J. M., & Wieland, M. M. (2009). Publicly traded versus privately held: implications for conditional conservatism in bank accounting. *Review of Accounting Studies*, 14(1), 88-122.

Nicoletti, A. (2018). The effects of bank regulators and external auditors on loan loss provisions. *Journal of Accounting and Economics*, 66(1), 244-265.

Nkusu, M. (2011). Nonperforming Loans and Macrofinancial Vulnerabilities in Advanced Economies. IMF Working Paper, WP/11/161. Available at: https://www.imf.org/~/media/Websites/IMF/imported-full-text-pdf/external/pubs/ft/wp/2011/_wp11161.ashx

Pan, Y. (2017) The Determinants and Impact of Executive-Firm Matches. *Management Science*, 63 (1), 185-200.

Peria, M. S. & Schmukler, S. L. (2001). Do Depositors Punish Banks for Bad Behavior? Market Discipline, Deposit Insurance, and Banking Crises. *The Journal of Finance*, 56(3), 1029-1051.

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *The Review of Financial Studies*, 22(1), 435-480.

Petrella, G., & Resti, A. (2013). Supervisors as information producers: Do stress tests reduce bank opaqueness? *Journal of Banking & Finance*, 37(12), 5406-5420.

Pitcher, P., & Smith, A. D. (2001). Top management team heterogeneity: Personality, power, and proxies. *Organization Science*, 12(1), 1-18.

Podpiera, J., & Weill, L. (2008). Bad luck or bad management? Emerging banking market experience. *Journal of Financial Stability*, 4(2), 135-148.

Sahin, C., & de Haan, J. (2016). Market reactions to the ECB's Comprehensive Assessment. *Economics Letters*, 140, 1-5.

Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, 22(3), 203-224.

Schoar, A., & Zuo, L. (2017). Shaped by booms and busts: How the economy impacts CEO careers and management styles. *The Review of Financial Studies*, 30(5), 1425-1456.

Schrand, C. M., & Zechman, S. L. (2012). Executive overconfidence and the slippery slope to financial misreporting. *Journal of Accounting and Economics*, 53(1-2), 311-329.

Schweitzer, R., Szewczyk, S. H., & Varma, R. (1992). Bond rating agencies and their role in bank market discipline. *Journal of Financial Services Research*, 6(3), 249-263.

Shroff, N., Verdi, R. S., & Yost, B. P. (2017). When does the peer information environment matter? *Journal of Accounting and Economics*, 64(2-3), 183-214.

Skinner, D. J. (2008). The rise of deferred tax assets in Japan: The role of deferred tax accounting in the Japanese banking crisis. *Journal of Accounting and Economics*, 46(2-3), 218-239.

Steffen, S. (2014). Robustness, Validity and Significance of the ECB's Asset Quality Review and Stress Test Exercise. Working Paper. Retrieved from https://papers.ssrn.com/abstract=2517361

Stigler, George J. (1971). The theory of economic regulation. *The Bell Journal of Economics and Management Science* 2(1), 3-21.

Van Peteghem, M., Bruynseels, L., & Gaeremynck, A. (2018). Beyond diversity: A tale of faultlines and frictions in the board of directors. *The Accounting Review*, 93(2), 339-367.

Veblen, T. (1900). The Preconceptions of Economic Science III, *Quarterly Journal of Economics*, 14(2), 240-269

Verrecchia, R. E. (2001). Essays on Disclosure. *Journal of Accounting and Economics*, 32(1-3), 97-180.

Volkens, A., Krause, W., Lehmann, P., Matthiess, T., Merz, N., Regel, S. & Wessels, B. (2019): The Manifesto Data Collection. Manifesto Project (MRG/CMP/MARPOR). Version 2019a. Berlin: Wissenschaftszentrum Berlin für Sozialforschung (WZB).

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica*, 57(2), 307-333.

Wahlen, J. M. (1994). The nature of information in commercial bank loan loss disclosures. *The Accounting Review*, 69(3), 455-478.

Wells, K. (2020). Who manages the firm matters: The incremental effect of individual managers on accounting quality. *The Accounting Review*, 95(2), 365-384.

Whalen, G. (1991). A proportional hazards model of bank failure: an examination of its usefulness as an early warning tool. *Economic Review*, 27(1), 21-31.

Whited, T. M. (2006). External finance constraints and the intertemporal pattern of intermittent investment. *Journal of Financial Economics*, 81(3), 467-502.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. MIT press. Cambridge, MA.

Yang, H. I. (2012). Capital market consequences of managers' voluntary disclosure styles. *Journal of Accounting and Economics*, 53(1-2), 167-184.

Young, S. M., Du, F., Dworkis, K. K., & Olsen, K. J. (2016). It's all about all of us: The rise of narcissism and its implications for management control system research. *Journal of Management Accounting Research*, 28(1), 39-55.

Curriculum Vitae

Nicolas Rudolf

Doctoral Candidate at the University of Mannheim

PhD, Accounting	2014 to 2020
University of Mannheim, Mannheim, Germany	
Goethe University, Frankfurt am Main, Germany	
Committee: Jannis Bischof, Holger Daske	
Visiting PhD, Accounting	2017
Lancaster University Management School, Lancaster, UK	
Master of Science, Management	2011 to 2014
Goethe University, Frankfurt am Main, Germany	
Major: Accounting & Information Management	
Bachelor of Science, Management and Economics	2007 to 2011
Ulm University, Ulm, Germany	
Major: Accounting and Auditing	