Managerial incentives, earnings management and regulatory intervention in the banking sector

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Erklärung

Ich erkläre, dass ich die Arbeit selbständig verfasst, keine anderen als die angegebenen Quellen und Hilfsmittel benutzt, die diesen Quellen und Hilfsmitteln wörtlich oder sinngemäß entnommenen Ausführungen als solche kenntlich gemacht habe und die Arbeit bisher noch keiner anderen Prüfungsbehörde vorgelegt wurde.

Würzburg, den 31. Januar 2018

Deutsche Zusammenfassung

Aktuell spielen Banken in allen funktionierenden Volkswirtschaften eine stetig wachsende Rolle, da sie sowohl für Haushalte als auch für Unternehmen eine zentrale Funktion erfüllen: Finanzintermediation. Trotz dieser wichtigen Aufgabe ist die Stabilität des Finanzsystems nicht grundsätzlich gesichert. Dies offenbarte sich in der jüngsten Finanzkrise. Infolgedessen nahm die Aktivität von Regulierungsbehörden gleichsam mit der wachsenden Bedeutung zu.

Der Fokus auf den Bankensektor der Regulationsbehörden ergibt sich durch die Funktion der Finanzmediation. Diese besteht grundsätzlich aus Vermittlungs- und Transformationsleistungen.

Beide sind essentiell aufgrund der asymmetrischen Informationsverteilung der wirtschaftlichen Realität, die eine kostenintensive Informationsbeschaffung für Investoren erfordert. Banken haben mittels ihrer Intermediation zweierlei Möglichkeiten die Informationskosten zu senken: das Realisieren von Skaleneffekte und die Eliminierung redundanter Informationsbeschaffung. Die in einer Second-best Welt auftretenden Agency-Kosten werden somit reduziert. Jedoch ist anzumerken, dass Banken selbst nicht unempfänglich für Agency-Probleme sind. So gelingt es ihnen oftmals nicht die Kosten der Risikoübernahme, bzw. die Vorteile ihrer Überwachungserfolge vollständig zu internalisieren.

Als Reaktion auf diese Problematik werden Banken von Behörden reguliert und von Aufsichtsräten kontrolliert. Das bedeutet allerdings nicht, dass Banken dem Eingriff beider Gruppen ohne Maßnahmen zur Einflussnahme ausgeliefert sind. Die gezielte Ertragssteuerung bietet eine Möglichkeit dem entgegen zu wirken. Hierbei werden Spielräume in der Rechnungslegung genutzt, um Ziele zu erreichen, die nicht unbedingt der Gewinnmaximierung dienen. Somit kann eine gezielte Ertragssteuerung genutzt werden, um Kapitalvorschriften zu erfüllen oder Gewinnglättung zu erzielen.

Die vorliegende Dissertation befasst sich mit drei Themen, die direkt und indirekt innerhalb dieses Themenkomplexes miteinander verknüpft sind: Fehl-/Anreize und Risikoübernahme, Ertragssteuerung und die Regulierung von Aufsichtsräten.

Kapitel zwei behandelt die Studie „Do cooperative banks suffer from moral hazard behaviour? Evidence in the context of efficiency and risk“. Diese beschäftigt sich mit dem Einfluss von Anreizen und Kompetenzen des Bankmanagements auf die Risikoübernahme von Banken.

Durch technischen Fortschritt, Deregulierung und die Einführung des Euros als Gemeinschaftswährung sehen sich Banken mit zunehmender Konkurrenz konfrontiert. Dies führt zur Notwendigkeit die Effizienz zu erhöhen, um die Marktposition zu halten. Um dieses Ziel zu erreichen versuchen Banken ihre Input-Output-Relation zu verbessern, indem sie sich an Best-Practice-Ansätzen orientieren. Andererseits können Banken ihre Kosten senken, indem sie die eingegangenen Risiken erhöhen. Seltene beziehungsweise weniger tiefgründige Anwendungen von Risikomanagementwerkzeuge wie beispielsweise Screening oder Monitoring helfen dabei. Berger und DeYoung (1997), Williams (2004) und Fiordelisi et al. (2011) untersuchten in diesem Kontext verschiedene Zusammenhänge zwischen Effizienz, Risiko und Bankkapital und zeigen, dass Banken mit niedriger Kosteneffizienz auch Probleme mit der Risikosteuerung aufweisen. Zum anderen kann eine hohe Kosteneffizienz auch durch die Reduzierung von Risikosteuerungsmaßnahmen erreicht werden, was sich allerdings auf die Qualität des Kreditportfolios auswirkt. Allerdings kann die Wirkbeziehung zwischen Effizienz und Risiko auch in die entgegengesetzte Richtung verlaufen: Exogene Schocks wirken sich negativ auf die Kreditportfolioqualität aus, was ein kostenintensives Eingreifen des Managements erfordert. Schließlich kann das Management moralischem Risiko ausgesetzt sein. welches zu einer Erhöhung des eingegangenen Risikos führt, sollte die Bank ein niedriges Eigenkapitalniveau aufweisen.

Insbesondere der letzte Zusammenhang wird im Forschungspapier beleuchtet, da Genossenschaftsbanken im Fokus stehen. Angesichts dessen, dass ihr Geschäftsmodell nicht auf Gewinnmaximierung, sondern auf Förderung der Interessen der Anteilseigner abzielt, sollten kurzfristige Gewinnerzielungsabsichten der Eigner nicht zum Tragen kommen.

Für die Untersuchung werden 205 bayrische Genossenschaftsbanken von 2007 bis 2014 betrachtet, wobei die Beziehung zwischen Effizienz, Kapital und verschiedenen Risikokennzahlen (Bankkapital-, Kredit und Liquiditätsrisiko) im Zentrum der Arbeit stehen. Die Ergebnisse deuten darauf hin, dass eine niedrige Effizienz mit einem Anstieg des Liquiditätsrisikos einhergeht. Des Weiteren zeigen die Resultate einen Zusammenhang zwischen einem Anstieg des Kreditrisikos und Absinken des Effizienzniveaus. Das bedeutendste Ergebnis ist jedoch, dass die Erwartung bezüglich des moralischen Risikos bestätigt wurden: Ein Absinken des Eigenkapitalniveaus führt zu einem niedrigeren Risikoniveau.

In Kapitel drei kommen wir auf die Ertragssteuerung zurück. Im Forschungspapier „Earnings Management Modelling in the Banking Industry – Evaluating valuable approaches“ werden die Methoden zur Abschätzung des Ausmaßes an Ertragssteuerung im Bankensektor untersucht. Während die Rechnungslegungsforschung den methodischen Bereich der Ertragssteuerung bei Industrieunternehmen profund untersucht hat, ist dieser Forschungsstrang in Bezug auf Banken deutlich weniger tief ausgeprägt. Da das Ausmaß an Ertragssteuerung jedoch nicht direkt beobachtet werden kann, sondern mit Hilfe von Regressionsmodellen abgeschätzt werden muss, ist diese Lücke äußerst problematisch.

Um zu klären, welche Variablen obligatorisch für ein optimal angepasstes Regressionsmodell sind, und ob statische oder dynamische Modelle besser geeigneter sind, werden in der vorliegenden Studie 430 US-Banken zwischen 2005 und 2015 untersucht. Die sich daraus ergebenen Proxy-Variablen werden im zweiten Schritt unter Zuhilfenahme von etablierten Testprozeduren auf Messfehler, Verzerrungen und Vorhersagekraft untersucht.

Die Ergebnisse deuten darauf hin, dass ein tiefgehendes Verständnis bezüglich der Modellierung der Regressionsgleichungen nötig ist, da aktuell verwendete Modelle zur Abschätzung des Ausmaßes an Ertragssteuerung zwar grundsätzlich angemessen sind, jedoch auch Optimierungsbedarf aufweisen.

Ebenfalls ersichtlich ist, dass der Wert notleidender Kredite die wichtigste Größe für die Modellierung der Regressionsgleichung darstellt. Zwar hat das Ausmaß der Risikovorsorge und Netto-Abschreibungen Einfluss auf die Regressionsergebnisse. Dieser ist jedoch stark von dem zu schätzenden Modell abhängig. Weiterhin wird deutlich, dass einige Zusammenhänge eher nicht linear sind, in den aktuellen Modellen jedoch linear dargestellt werden. Zusätzlich konnten weitere Variablen identifiziert werden, welche die Güte der Regressionsmodelle erhöhen können. Bezüglich der Vorhersagekraft der Modelle zeigt sich, dass besser spezifizierte statische Modelle verlässlichere Proxy-Variablen erzeugen.

Das letzte Kapitel der Arbeit mit dem Namen „Board Regulation and its Impact on Composition and Effects – Evidence from German Cooperative Bank“ beschäftigt sich mit den Auswirkungen von Aufsichtsratregulierungen in zweierlei Kontext: Zum einen wird ihr Einfluss auf die Struktur des Aufsichtsrats untersucht, zum anderen der Effekt des Aufsichtsrates auf verschiedene Risikogrößen nach Einführung der Regulierung. Die Regulierung, die im Zentrum dieses Forschungspapiers steht, ist das Gesetz zur Stärkung der Finanzmarkt- und Versicherungsaufsicht (FinVAG). Dieses Gesetz befähigt die Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) Einfluss auf Aufsichtsräte zu nehmen. Die BaFin darf seit der Einführung 2009 Aufsichtsräte und einzelne Mitglieder selbiger Eignungsprüfungen unterziehen, um ihre Kompetenz und Zuverlässigkeit zu prüfen. Das Ziel hierbei ist die Sicherstellung der Kontrollfähigkeit von Aufsichtsräten durch Festlegung eines gewissen Kompetenzniveaus und Bankenverständnisses.

Hierfür werden in der vorliegenden Studie 246 bayrische Genossenschaftsbanken zwischen 2006 und 2011 betrachtet, um Einblicke in Bezug auf zwei Problemstellungen zu gewinnen. Zum einen soll die Auswirkung des FinVAG auf die Aufsichtsratstruktur in Bezug auf den beruflichen Hintergrund und Anteil an Promovierten untersucht werden. Zum anderen werden die Auswirkungen verschiedener Aufsichtsratcharakteristika auf zentrale Risikogrößen untersucht. Bestimmten Personengruppen wie Wirtschaftsprüfern und Promovierten ist ein potenziell besseres Bankenverständnis unterstellbar. Ein Aufsichtsrat, der diese Personengruppen stärker repräsentiert, kann folglich eine bessere Kontrollfunktion signalisieren, welche wiederum eine öffentlich angekündigte Untersuchungsprozedur der BaFin verhindern kann. Dies ist besonders interessant im Hinblick auf die untersuchten Genossenschaftsbanken, welche historisch bedingt mit überwiegend Landwirten im Aufsichtsrat eine hohe Wahrscheinlichkeit der Umstrukturierung aufweist.

Die Ergebnisse deuten darauf hin, dass es zwar keine signifikante Erhöhung der Aufsichtsratumstrukturierungen, Promovierten und Berufskonzentration gab. Allerdings lässt sich eine signifikante Verschiebung von nicht-ökonomischen Berufen zu ökonomischen Berufen zeigen. Bezüglich der Auswirkungen auf Risikogrößen zeigt sich, dass die Einführung des FinVAG durchaus erfolgreich war. Aufsichtsratcharakteristika, die sich vor Einführung risikoerhöhend ausgewirkt haben, wirken sich seitdem zum größten Teil risikosenkend aus. Dementsprechend erfüllt das FinVAG seine angedachte Wirkung.

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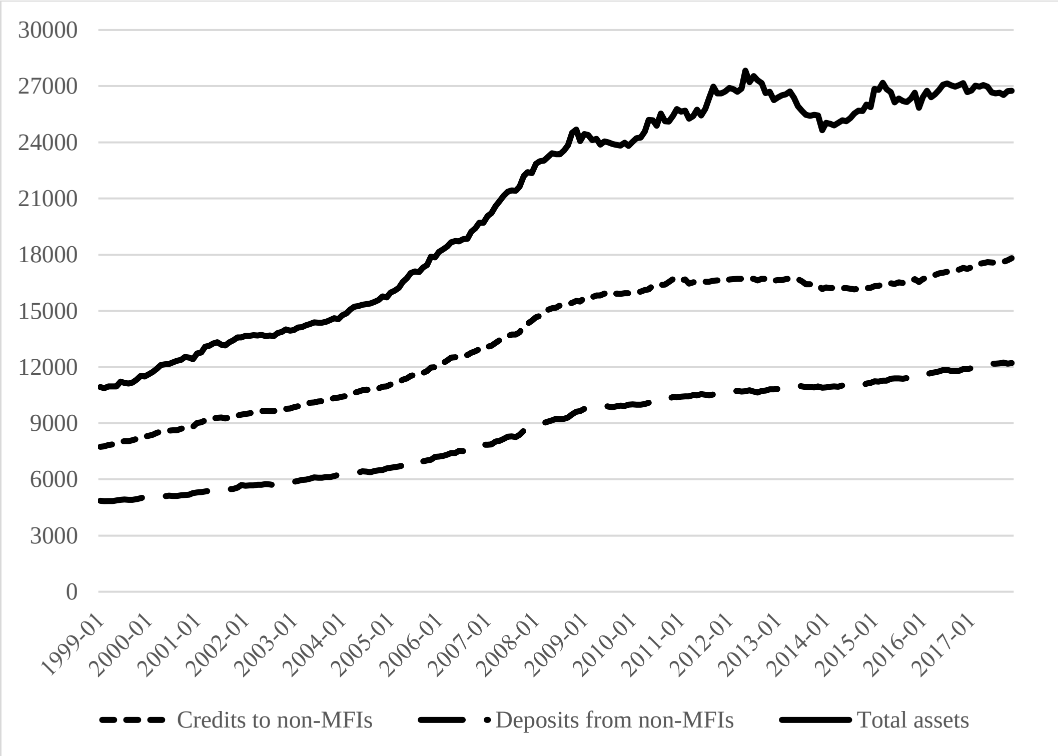
1 Introduction and summary

Nowadays, the banking sector plays an ever-increasing role in every functional economy as they provide financial intermediation services for households and firms. Despite the important role financial stability is not always in a satisfactory condition as various events like the financial crisis revealed. Consequently, as the importance of banks increased, the regulatory efforts intensified alike. The increase in importance as well as the increase in regulatory intervention are both depicted well by two developments: First, the increase in credits to and deposits from non-monetary financial institutions (MFI) and total assets. Second, the amount of regulatory effort represented by the number and extent of regulatory documents. Figure 1.1 and Figure 1.2 show the development of credits to non-MFIs, deposits from non-MFIs and total assets of the European respectively German banking sector since 1999. The numbers show that credits, deposits and total assets steadily increased with a few exceptions (EU 2013 until 2015, Germany 2012 until 2015). The same statement holds true in regard to regulatory efforts. Kolly et al. (2017) analyze 163 regulating documents (including Basel I, II and III) issued by the Basel Committee on Banking Supervision (BCBS) prior to August 2017. For this purpose, the authors examine various aspects, namely amount of text, complexity, grammar structure, risk definition and regulatory instruments. Their results show that the amount of text, complexity of wording and number of formulations with a binding effect increased.[1] Also, the focus regarding various risk categories changed over time. While operational and liquidity risks were widely neglected until 2003, they became more relevant, especially during the financial crisis in 2007 and 2008. Regarding regulatory instruments the authors show that capital requirements are the central measure to influence banks. However, since the financial crisis these measures were complemented by new forms of capital and liquidity requirements as well as supervisory checks.

[1] After all, the majority of formulations consist of non-binding proposals incorporated by applying the wording "should". It follows that banking regulation is implemented mainly by recommendations, not obligations.

Figure 1.1

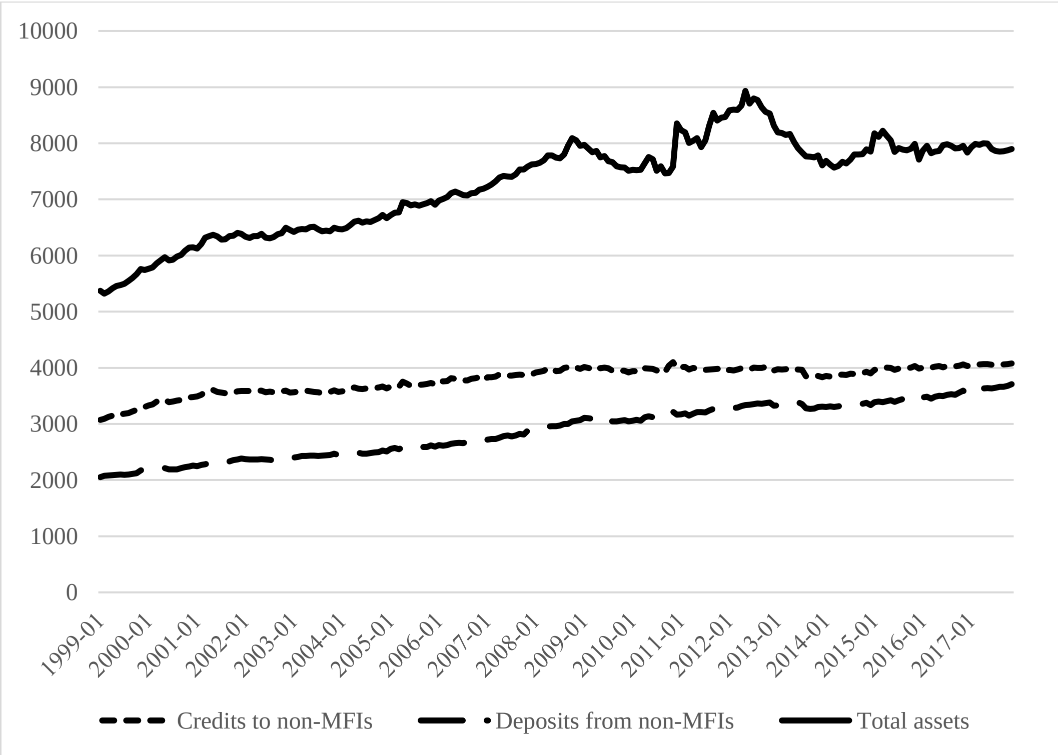
Development of credits, deposits and total assets for EU banks



In billion €   Source: German Central Bank

Figure 1.2

Development of credits, deposits and total assets for German banks



In billion €   Source: German Central Bank

The focus of regulatory institutions on banks is not surprising as they provide a central function for the real economy: financial intermediation. In more detail, financial intermediation consists of two services which are the core functionality of banks in general: Brokerage and qualitative asset transformation (QAT). While the brokerage aspect consists of, for instance, transaction services and financial advice, the QAT is attribute modification like maturity transformation or risk diversification (Bhattachary and Thakor, 1993).

Both functions are especially interesting from a theoretical and scientific point of view, since both are unnecessary under the assumption of complete markets. In a first-best-world, households are indifferent between bank deposits and securities, while firms are indifferent between bank loans and securities. Hence, financial intermediation is not necessary (Santos, 2001). Therefore, it is not surprising that microeconomic theory of banking was non-existent up until the 1980s (Freixas and Rochet, 2008).

However, the economic reality is not describable as a first-best-world in which complete markets are ubiquitous. Issues such as information asymmetry make first-best-world solutions inapplicable. For instance, information about business conditions is asymmetrical distributed between households and firms. Without (costly) information procurement households are not able to make sound investment decisions. It follows that banks performing their financial intermediation functions are able to reduce information costs as they realize comparative advantages relying on scale economies and the elimination of repeated investors' monitoring costs. (Diamond, 1984; Freixas and Rochet, 2008). Therefore, the described agency problems are partial reduced by the involvement of banks. Nonetheless, banks are not insusceptible regarding agency problems. Beatty and Liao (2014) state that banks are often not able to "*fully internalize either the cost of their risk taking or the benefit of their monitoring efforts".* Incentives to take risks differ heavily when bank managers, shareholders and depositors are considered. This divergence may lead to suboptimal risk allocation. This problem is further amplified by regulatory guidelines, as most (risky) asset classes directly influence regulatory capital ratios negatively by increasing risk-weighted assets. Consequently, banks are incentivized to take more risks to increase income and therefore regulatory capital.

If capital regulation amplifies the problem regarding optimal risk allocation, why is regulatory effort increasing and not diminishing? From a modern perspective the answer is apparent with financial crisis and European credit crisis being not long ago. Banks need to be regulated as:

- Outsiders are not able to value banks correctly due to lagged and inaccurate information, which in turn cause the failure of usual market control mechanisms (Flannery et al., 2004)
- If unregulated, banks tend to underprovision the need of liquidity services which makes bank vulnerable to bank runs (Diamond and Dybvig, 1983)
- Bank regulation forces banks to "internalize losses, thereby protecting the deposit insurance fund mitigating moral hazards" and controls "social costs associated with excessive balance sheet shrinkage of multiple financial institutions hit with a common shock." (Hanson et al., 2011)

For all that, banks have various means at hand to mitigate the actual impact of regulatory interventions. One of the measures is earnings management, which describes the usage of discretion to share earnings in a way, which is not motivated by information transparency but opportunistic objectives, such as realisation of capital requirements or earnings smoothing (Morgan, 2002; Shen and Chih, 2005).

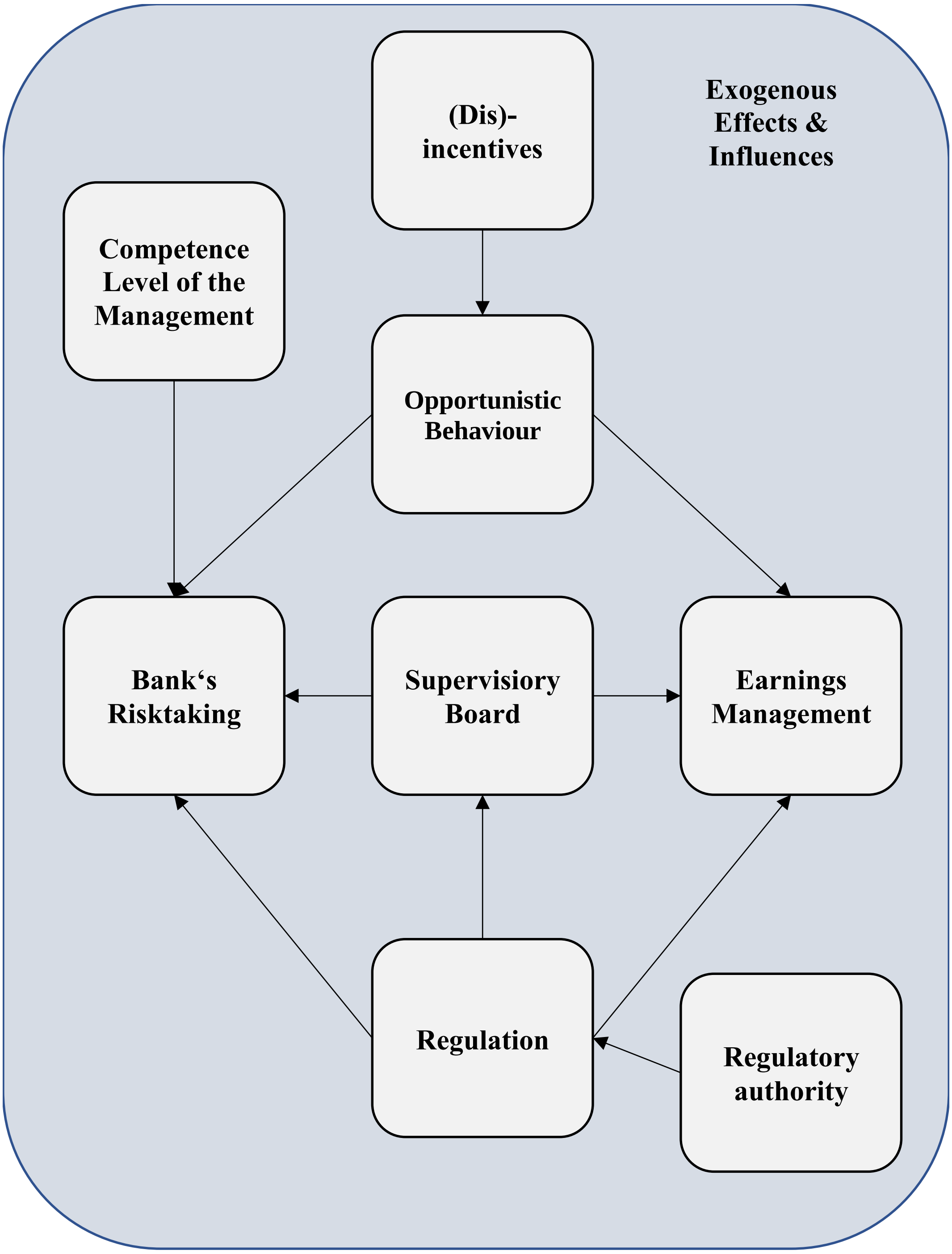
The present dissertation focuses on three of the mentioned topics: (Dis-)incentives and risk taking, earnings management and regulation of supervisory boards. The opening words up to this point should make it apparent that all of these topics are connected. Figure 1.3 illustrate the relationship between dissertation topics. In this illustration, banks' risk-taking is influenced mainly by five forces. The competence level of bank managers directly influences the exposure to risk. Berger and DeYoung (1997) show that poor bank managing is reflected by low cost efficiency and ineffective monitoring of debtors, which influences the loan quality, hence credit risk negatively. However, the opposite might also be true, as the authors elaborate their cost-skimping hypothesis. In this situation bank managers pursue myopic interests by cutting monitoring cost. This short-term performance boost is achieved at the expense of long term loan quality. Yet, risk-taking is not the only way in which opportunistic behaviour may arise.

As mentioned above, banks are under a constant regulatory pressure regarding capital requirements and accounting practises. To circumvent requirements banks may utilise their potential discretion to manage their earnings in a way, which benefits them (Shen and Chih, 2005). However, capability to engage in earnings management is heavily dependent on the current accounting regime, which changes over time[2].

The accounting regime is not the only limiting factor in regard to earnings management. Supervisory boards fulfil the function of representing and protecting the interest of shareholders, hence are eager to prevent a deluded representation of the state of the bank (Pathan, 2009). This holds true also regarding bank risk-taking. However, in the recent past supervisory boards and non-executive board member were not always able to fulfil their consulting and monitoring function. Therefore, regulatory institutions like the German Federal Financial Supervisory Authority BaFin were empowered to check supervisory boards in regard to competence and reliability. This regulatory pressure is intended to fulfil an incentivizing effect, which in turn should improve the monitoring efforts, eventually increasing financial stability.

[2] Beatty and Liao (2014) summarized the accounting implications of various states of accounting regimes on capital requirements and especially risk provisioning.

Figure 1.3
Relationships between dissertation topics



Chapter two focuses on the first topic: the influence of managerial competence and incentives on risk. Since banks are facing rising competition due to technological development, deregulation and the introduction of the Euro as a common currency, they are forced to improve their efficiency to remain competitive. To increase their efficiency banks, try to improve their input- output relation, hence operating in accordance to best practice. Anyhow, banks are also able to decrease their costs by increasing the risk-exposure by reducing the usage of risk-management tools like screening or monitoring. Regarding these possibilities various authors (especially Berger and DeYoung (1997), Williams (2004) and Fiordelisi et al. (2011)) try to establish coherences between efficiency, risk and capital. Their findings indicate that banks with low cost-efficiency (due to a bad management performance) are unable to monitor their loan portfolio, leading to a decrease in loan quality. On the other hand, high cost-efficiency may be the result of cost cuts in loan quality measures like monitoring. However, loan quality may be negatively influenced by exogenous events (like the recent financial crisis), which in turn lead to a decrease in efficiency, due to cost related to the monitoring of distressed debtors. Finally, banks may engage in moral hazard and increase their risk expose in presence of a low equity-ratio.

Especially the last potential relationship is interesting, when cooperative banks are investigated. Their business model is not based on the maximization of returns but characterized by a focus on the interests and prosperity of the local customers and members (see § 1 GenG). Therefore, moral hazard incentives should not apply to cooperative banks, since short-term shareholder interests (which in turn create the earnings-pressure on bank managements) are not relevant.

To gain insights the study uses a sample of 205 Bavarian cooperative banks between 2007 and 2014 to investigate the relationship between capital, efficiency and various measures of risk (namely capital-, credit-, and liquidity risk). Liquidity risk was neglected in previous literature but became more relevant in consideration of events like the financial crisis and the resulting mistrust in the banking sector.

Results indicate that low efficiency is related to an increase in liquidity risk. In addition, we find that an increase in credit risk is related to a decrease in efficiency. Most important the study shows that moral hazard incentives are not relevant in cooperative banking. Results show a positive relationship between equity and credit risk indicating a decrease in risk expose in presence of low equity-ratios.

Chapter three examines methods of Earnings Management measurement. While accounting literature has extensively investigated the field of Earnings Management for all industries, the approaches in banking literature are less comprehensive. In consideration of the fact that Earnings Management is not directly observable but needs to be estimated by applying well developed regression models, a lack of discussion in regard to technical issues is problematic. Therefore, the study employs a US based dataset with 430 banks from 2005-2015 to find answers for the questions, which regressors are mandatory for the estimation of well fitted Earnings Management proxies and whether dynamic or static approaches should be applied. To gain insights the study employs various well-established test procedures to examine the extent of measurement errors, extreme performance and omitted-variable biases and predictive power of the discretionary proxies of each of the models.

The results indicate that a thorough understanding regarding the modelling process of EM in the banking industry is mandatory, as currently applied EM models seem to be appropriate yet optimizable. To be precise, the study shows that non-performing assets are the most important variables when it comes to the modelling of EM models. Loan loss allowance and net charge offs on the other hand seem to add some value, which is highly dependent on the overall specified model. Furthermore, the results indicate that non-linearity of certain regressors can be an issue which should be addressed in future research. In addition, the results show significant effects for some variables in the omitted-variable regression. Therefore, these variables should also be addressed in future research. Regarding predictive power the results indicate that better specified models can produce EM proxies, which in turn are more reliable in terms of predicting actual EM behavior.

Finally, Chapter four deals with effects of regulation on supervisory board structure and the impact of supervision board characteristics on various risk measures. Recent events, like the financial crisis, casted a shadow on the state of supervisory board in regard to their control and monitoring function. With the implementation of the German Act to Strengthen Financial Market and Insurance Supervision (FinVAG) the German Financial Supervisory Authority (BaFin) was empowered to influence supervisory boards more directly. BaFin is now authorized to check supervisory boards and in particular individual member for their level of competence and reliability. The intension is to ensure functional governance mechanisms by enforcing a certain level of competence and understanding of the banking business. Consequently, two effects should be observable regarding supervisory board structure and the effects of supervisory board characteristics on risk. First, since investigations of BaFin are publicly announced and therefore connected to reputation losses, it is beneficial to prevent such scenarios by signaling good governance through a supervisory board structure, which is characterized by high economic knowledge. Therefore, supervisory board which do not already fulfil this requirement should face very specific restructurings in regard to occupational backgrounds. Second, as BaFin is enabled to direct removals from office, this threat should incentivize members of supervisory boards to fulfil their control and monitor function to the fullest they are capable of. Especially the first effect is interesting regarding the investigated type of banks – cooperative banks. Since the historical development of cooperative banks is linked to rural regions, supervisory boards often consist of economically important persons, such as farmers. It can be assumed that the potential to understand complex relationships in banking and financial markets is very highly correlated with the extend of economic background. Therefore, very distinctive changes in supervisory board composition are to be expected.

To gain insights the study uses a sample of 246 Bavarian cooperative banks between 2006 and 2011 to investigate the influence of the implementation of FinVAG on supervisory board structure and on the effects of board characteristics on various risk measures. As FinVAG was implemented to improve supervisory capabilities, board characteristics of interest are occupational backgrounds, share of Ph.D. degree holders and occupational concentration. Concerning supervisory board structure, the study investigates the consequences of FinVAG in regard to the occupational and educational structure pre- and post-FinVAG. In addition, it is investigated to which extent historically grown features are dissolved and replaced by a more common supervisory board structure. Regarding the impact on risk measures, the study applies all measures, which are targeted in the legal text of FinVAG, namely credit-, equity-, liquidity-risk and in addition the Z-Score.

Results indicate that although there is no significant increase in structural board changes, Ph.D. degree holder share and occupational concentration, there is a significant shift from non-economic to economic backgrounds. Regarding the effects of board characteristics on various risk measures, results show, that the implementation of FinVAG was in a way successful. While the effects of Ph.D. degree holder share and occupational concentration in the pre-FinVAG period are, with only very few exceptions, risk increasing, interaction effects, indicating the influence after the implementation of FinVAG, are risk decreasing. Therefore, the implementation of FinVAG fulfilled its intended impact.

2 Do cooperative banks suffer from moral hazard behaviour? Evidence in the context of efficiency and risk[3]

2.1 Introduction

In recent decades, there has been increasing competition in the European banking market due to technological development, deregulation and the introduction of the euro as a common currency. To remain competitive, banks have been forced to improve their efficiency – that is, they try to operate closer to a “best practice” production function by improving their input-output relation. The key question in this context is whether banks improve their efficiency at the cost of higher risk to compensate decreasing earnings. Regarding risk, a large strand of literature discusses the issue of problem loans. Several studies identify that banks hold large shares of non-performing loans in their portfolio before becoming bankrupt (Demirgüc-Kunt, 1989; Barr et al., 1994). Regarding efficiency, studies show that the average bank generates low profits and incorporates high costs compared to the “best practice” production frontier (Williams, 2004; Fiordelisi et al., 2011). At first glance, these two issues do not seem to be related. However, Berger and DeYoung (1997) show that banks with poor management are less able to handle their costs (low cost efficiency) and to monitor their debtors appropriately in order to ensure loan quality. The negative relationship between cost efficiency and non-performing loans leads to declining capital, which in turn may push banks into bankruptcy. Thus, regulators try to counterbalance these issues by requiring banks to hold a certain amount of capital. Nevertheless, deposit insurance and limited liability combined with increased competition may lead banks to take on more risk (Goddard and Wilson 2009). For this reason, it is of high importance for regulators to understand economic causation in terms of efficiency, risk and capital in order to impose appropriate capital controls and thus to prevent negative consequences in the banking market.

[3] This chapter is based on a working paper titled “Do cooperative banks suffer from moral hazard behaviour? Evidence in the context of efficiency and risk” (Reeg and Stralla, 2016), which is co-authored by Dr. Johannes Reeg.

We delve deeper into these ties first by addressing the relationship between efficiency and risk. For instance, banks may be inclined to increase efficiency by lowering their expenditures used for, e.g., customer evaluation or credit monitoring. Regarding this scenario, increases in bank efficiency may precede increases in non-performing loans. Similarly, economic downturns may negatively affect bank efficiency: increases in non-performing loans may precede decreases in bank efficiency as banks need to supply additional funds in order to handle increasing problem loans. Second, we address how these issues are related to bank capital. For instance, banks with low efficiency are less able to build up capital. Moreover, limited liability and deposit insurance might cause banks to increase risk. Another possible case is that banks hold low amounts of capital because they are efficient. High efficiency enables these banks to build additional capital if needed. Alternatively, banks may hold high capital because they are highly efficient. As these banks do not benefit by building additional capital, they might increase risk to compensate for holding expensive capital. We therefore address these issues by explicitly investigating the intertemporal relationships among efficiency, risk and capital.

We contribute to the literature in several ways. First, we use contemporaneous data of cooperative banks in Bavaria from 2007 to 2014. The sample period covers the financial crisis and the recent euro sovereign debt crisis. Cooperative banks weathered these crises better than other banks. There may be some reasons: For instance, the business model of cooperative banks is based on the interests of their customers, who are commonly locals (the cooperative act: § 1 GenG). Thus, we expect that the common perception of banks engaging in moral hazard behaviour may not apply to cooperative banks. Short-term shareholder interests (as a potential contributing factor for moral hazard behaviour) play no role for cooperative banks, which may support this notion. Moreover, due to their local focus, cooperative banks exhibit a risk profile much different from that of commercial banks. For these reasons, we expect that the intertemporal relationships among risk, efficiency and capital of cooperative banks may partly differ from those of commercial banks. Second, cooperative banks (and banks with a similar business model, i.e., community banks or credit unions) play a major role in many developed countries. Surprisingly, literature examining those banks is scarce. Therefore, investigating this type of bank in terms of the relationships among efficiency, risk and capital may reveal helpful insights for, e.g., regulators or supervisors. Third, liquidity has been widely neglected in previous literature within this field because the common perception has been that access to additional liquid funds is not an issue. However, the recent financial crisis as well as the euro sovereign debt crisis revealed that liquidity dried up for many banks due to increased mistrust in the banking sector. For this reason, this study moves beyond the existing literature by employing a measure of liquidity risk to evaluate how liquidity risk is related to efficiency and capital.

The paper proceeds as follows: Section 2.2 reviews prior studies and provides relevant hypotheses. The efficiency models and the GMM-estimation technique are described in section 2.3. Section 2.4 provides information about the variables employed and descriptive statistics. Section 2.5 presents the results. The paper concludes with a summary of our most important findings.

2.2 Literature and Hypotheses

2.2.1 Literature Review

There are two major strands in the banking literature that started at the beginning of the 1990s. One of them addresses the determinants of bank risk and especially the determinants of bankruptcy (Whalen, 1991; Barr et al., 1994). The other one investigates factors of bank efficiency (Berger and Humphrey, 1992; Berger, 1993). Berger and DeYoung (1997) brings these two strands together by positing that bank risk and efficiency are related to each other. That is, when analysing the determinants of bank risk, one must consider efficiency and vice versa. The authors investigate US commercial banks between 1985 and 1994 with regard to the relationship between non-performing loans (as an indicator of bank risk) and cost efficiency. They also include bank capital in their analysis to show that problem loans and (cost) inefficiencies are associated with losses of capital. Thus, they apply Granger-causality methods to disentangle the intertemporal relationships among problem loans, cost efficiency, and capital. The two most important results are the bidirectional negative relationship between problem loans and cost efficiency. That is, that high proportions of problem loans precede decreases in cost efficiency, and banks with low cost efficiency perceive higher proportions of problem loans in upcoming periods.

Kwan and Eisenbeis (1997) confirm the view of Berger and DeYoung (1997) that bank risk, efficiency and capitalization are related and thus need to be investigated simultaneously. Thus, they analyse their sample of bank holding companies by estimating a simultaneous equations model using two-stage least-squares regressions. The authors identify a positive relation between inefficiency and bank risk. That is, banks with high efficiency are inclined to take less risk than low-efficiency banks. Moreover, they find that bank capital is positively related to inefficiency. They attribute this finding to effective regulation on the part of regulators. Consequently, both studies (Berger and DeYoung, 1997; Kwan and Eisenbeis, 1997) reveal that efficiency and capital are viable predictors of bank risk.

Williams (2004) introduces his study of European savings banks between 1990 and 1998 as a "robustness test" of the results of Berger and DeYoung (1997). Similar to Berger and DeYoung (1997), the author applies Granger-causality methods to investigate the relationships among problem loans, efficiency and capital. Due to data limitations, the author uses loan loss provision as a proxy for non-performing loans, and he employs the ratio of loans to assets as an indicator of credit risk. Moreover, he moves beyond the study of Berger and DeYoung (1997) by employing profit efficiency as a robustness test for cost efficiency. The results show that decreases in efficiency precede increases in problem loans. The author uses four-year lags and two-year lags and states that two-year lags are more appropriate for the underlying analysis.

Fiordelisi, et al. (2011) investigate in their study European commercial banks between 1995 and 2007. They analyse the relationships among efficiency (cost, profit and revenue), capital and bank risk. To the best of our knowledge, this is the only study to employ Granger-causality estimations in a GMM framework. Additionally, they use various measures of bank capital ([1] total capital as the sum of tier 1 and tier 2 capital and [2] book value of bank capital) and bank risk ([1] the classical measure of non-performing loans and [2] one-year-ahead and five-year-ahead expected default frequency (EDF) as a forward-looking measure of bank risk). The results indicate that decreases in cost and revenue efficiency precede higher bank risk and that increases in bank capital Granger-cause cost efficiency improvements. In addition, more efficient banks (cost and profit) lead to increases in bank capital, and higher capital levels Granger-cause higher efficiency.

Finally, the following two studies from Goddard et al. (2014) and Berger et al. (2009) analyse bank efficiency with regard to ownership type. Goddard et al. (2014) analyse the evolution of the average rank cost efficiency with a sample of 419 banks from Latin America over the 1985 to 2010 period. The authors apply different models ([1] random parameters models, [2] random effects models and [3] fixed effects models) for estimating cost efficiency. They state that random parameters models are better to address cross-firm heterogeneity when estimating cost efficiency. They identify differences across countries in terms of bank cost efficiency, and their results reveal differences in cost efficiency for state-owned, privately owned and foreign banks. Berger et al. (2009) analyse profit and cost efficiency differences with regard to ownership type by examining 38 Chinese banks between 1994 and 2003. They apply pooled estimations and find that foreign minority ownership increases efficiency (compared to non-foreign ownership). In terms of foreign ownership, foreign banks are the most profit efficient, followed by private domestic banks. State-owned banks appear to be the least efficient.

Overall, the extant banking literature in this field is clear. Berger and DeYoung (1997), Williams (2004) and Fiordelisi et al. (2011) are relevant studies that apply Granger causality to disentangle the relationships among risk, efficiency and bank capital. Berger and DeYoung (1997) and Williams (2004) both apply OLS estimations. However, OLS estimations may be problematic within this context due to endogeneity issues arising from the application of lagged variables. Fiordelisi et al. (2011) explicitly consider this issue and use a GMM framework for their estimations.

2.2.2 Research Hypotheses

In the following, we refer to relevant hypotheses for our study by building on the works of Berger and DeYoung (1997), Williams (2004) and Fiordelisi et al. (2011). To disentangle the intertemporal relationships among risk, efficiency and bank capital, we investigate the following hypotheses:

The “bad management” hypothesis assumes that banks with low cost efficiency (high costs due to an inefficient cost-management team) incorporate higher costs compared to the “best practice” production function. These costs appear immediately and lead to increases in bank risk (high share of non-performing loans) in upcoming periods. The assumption behind this hypothesis is that banks that are not able to manage their costs are also not able to ensure appropriate customer evaluation and credit monitoring, which will lead to an increase in non-performing loans in the future. This assumption may also apply to the level of liquidity. Particularly term transformation is one major task of a banks' management. The management should carefully manage short-term loans and deposits to ensure a sound level of liquidity in the near future. Regarding this issue, a myopic management may certainly lead to liquidity problems. Thus, we postulate our first hypothesis:

H1: Decreases in cost efficiency precede increases in bank risk.

The "bad luck" hypothesis assumes that economic downturns such as the financial crisis in 2007 induce higher shares of non-performing loans. As this hypothesis is based on exogenous events, changes in the loan portfolio are not related to managerial failures. However, increases in non-performing loans will cause managers to address these problems, which will result in rising costs. Consequently, the second hypothesis is:

H2: Increases in bank risk Granger-cause decreases in cost efficiency.

The "cost-skimping" hypothesis is related to bank cost efficiency. It supposes that bank managers might pursue short-term rather than long-term results. Specifically, bank managers are supposed to cut costs for, e.g., credit screening, which will result in a lower-quality loan portfolio in future periods. Given this scenario, banks appear to be efficient in controlling their costs at a cost of future bank risk. The "cost-skimping" hypothesis is as follows:

H3: Increases in cost efficiency precede increases in bank risk.

Lastly, we pose the "moral hazard" hypothesis, which is related to bank capital. It assumes that banks who incorporate a low level of capital are inclined to take on more risk. The justification for this assumption is agency conflicts between managers and shareholders in banks. Specifically, bank managers are inclined to take more risk than is in the best interest of the owners (especially when bank managers do not hold their own shares). Additionally, limited liability and deposit insurance programs may strengthen risk-taking incentives. On the contrary, banks with high levels of capital may have reduced "moral hazard" incentives and thus be inclined to take on less risk. Thus, we postulate the "moral hazard" hypothesis as follows:

H4: Decreases in bank capital precede increases in bank risk.

The paper proceeds by exemplifying the applied methodology before providing descriptive statistics and discussing the regression results.

2.3 Methodology

In accordance with previous studies in this field, we employ a two-step model to examine the relationships among bank risk, efficiency and capital. In the first step, we rely on the stochastic frontier approach (SFA) to estimate efficiency levels. The second step builds on the estimated efficiency levels and employs Granger-causality techniques to investigate the intertemporal relationships among bank risk, capital and efficiency.

2.3.1 Measuring Efficiency

To estimate the efficiency levels, we employ SFA following Battese and Coelli (1995).[4] For cost efficiency, we estimate the following model:

$$ln\,TC_{i,t} = x_{i,t}\beta + (V_{i,t} + U_{i,t}) \tag{1}$$

where i specifies the bank, t denotes the time dimension, TC is total costs, x_i is a $m\ x$ 1 vector of input prices and outputs involved in the ith bank operations, β is a 1 $x\ m$ vector consisting of coefficients yet to be estimated. Error term $\varepsilon_{i,t}$ consists of two components, V_i and U_i. V_i represents random error, which is assumed to be i.i.d. with $N(0, \sigma_V^2)$ and is not correlated with U_i. U_i is the inefficiency term, which is assumed to be i.d.d., non-negative and follows a truncated normal-distribution with $N(\mu_U, \sigma_U^2)$. As in existing literature, we use a translog function form to estimate the frontier:

[4] We estimate the stochastic frontier using the Stata command *sfpanel* written by Belotti et al. (2012).

$$
\begin{aligned}
lnTC = {} & \alpha_0 + \sum_{j=1}^{3} \beta_j ln\, y_j + \sum_{j=1}^{3} \gamma_j ln\, w_j + \eta_1 E + \theta_1 T \\
& + \frac{1}{2}\Bigg[\sum_{j=1}^{3}\sum_{k=1}^{3} \beta_{jk}\, ln\, y_j\, ln\, y_k + \sum_{j=1}^{3}\sum_{k=1}^{3} \gamma_{jk}\, ln\, w_j\, ln\, w_k + \eta_{11} E^2 \\
& + \theta_{11} T^2\Bigg] + \sum_{j=1}^{3}\sum_{k=3}^{3} \lambda_{jk}\, ln\, y_j\, ln\, w_k + \sum_{j=1}^{3} o_j\, ln\, y_j\, E \\
& + \sum_{j=1}^{3} \rho_j\, ln\, y_j T + \sum_{j=1}^{3} \tau_j\, ln\, w_j\, E + \sum_{j=1}^{3} \varphi_j\, ln\, w_j T + ln\, v_{i,t} \\
& + ln\, u_{i,t}
\end{aligned}
\tag{2}
$$

i, t and TC remain defined as before. $y_j; y_k$ are outputs, $w_j; w_k$ are input prices, E is equity scaled by total assets, T is the time trend, $v_{i,t}$ is the random error term, and $u_{i,t}$ is the inefficiency term. Outputs are demand deposits (y_1), total loans (y_2) and other earning assets (y_3). Input prices are defined as personnel expenses scaled by total assets (w_1), depreciations scaled by fixed assets (w_2) and interest expenses scaled by total funds (w_3). In addition to variables included in equation (2), we use three environmental variables z_i, i.e., interest rate[5] (z_1), GDP growth (z_2) and unemployment rate (z_3), to simultaneously model the inefficiency distribution:

$$\mu_u = \psi_0 + \psi_1 z_1 + \psi_2 z_2 + \psi_3 z_3 \tag{3}$$

To ensure linear price homogeneity in the sense that a doubling of all input prices doubles total costs (Berger and Mester 1997), we apply five restrictions:

(1) Standard symmetry

$$\beta_{jk} = \beta_{kj}\,;\gamma_{jk} = \gamma_{kj} \tag{4}$$

(2) Coefficient constraints

$$\sum_{j=1}^{3} \gamma_j = 1\,;\ \sum_{j=1}^{3}\sum_{k=1}^{3} \gamma_{jk} = 0\,;\sum_{j=1}^{3}\sum_{k=1}^{3} \lambda_{jk} = 0 \tag{5}$$

[5] We calculate the ECB interest rate as daily weighted values for each year.

These restrictions are necessary to ensure linear price homogeneity by measuring cost efficiency. For profit efficiency, these constraints solely function to preserve the same functional form.

For estimating profit efficiency, we use the same model as in equation (2) but apply two modifications: Instead of the natural logarithm of total cost as a dependent variable, we use the natural logarithm of total profits. Since the natural logarithm is not defined for negative values, we handle that problem via the following positive monotone transformation: We add the sample minimum plus 1000 to total profits; thus, all values are positive. The second change concerns the sign of the inefficiency term. Banks with high cost inefficiency ceteris paribus have higher total costs and vice versa. Since profit inefficiency and total profits show a contrary relation, the sign of the inefficiency term turns negative if profit efficiency is measured.

By estimating equation (2), we use maximum likelihood estimations instead of OLS estimations for two reasons: First, the maximum likelihood estimator is more appropriate for small-sample estimations. Second, since the inefficiency part of the total error term is not normally distributed, the assumption of the OLS estimator regarding the distribution of the error term is not applicable (Kumbhakar 1990).

2.3.2 Estimating Intertemporal Relationships

Subsequently to our cost- and profit-efficiency estimations, we examine the intertemporal relationships among capital, efficiency and risk by applying Granger-causality techniques for the following equations:

$$\begin{aligned} LLP_{i,t} = & \left[\sum_{j=1}^{2} LLP_{i,t-j} \vee \sum_{j=1}^{2} LIQ_{i,t-j}\right] + \left[\sum_{j=1}^{2} \text{X-Eff}_{i,t-j} \oplus \sum_{j=1}^{2} \pi\text{-Eff}_{i,t-j}\right] \\ & + \sum_{j=1}^{2} \text{E/TA}_{i,t-j} + \text{TA}_{\text{i,t}} + \text{ID}_{\text{i,t}} + \text{MRISK}_{\text{i,t}} + \text{GDP}_{\text{t}} \\ & + \text{INTRATE}_{\text{t}} + \text{UNEMP}_{\text{t}} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

$$\begin{aligned} LIQ_{i,t} = & \left[\sum_{j=1}^{2} LLP_{i,t-j} \vee \sum_{j=1}^{2} LIQ_{i,t-j}\right] + \left[\sum_{j=1}^{2} \text{X-Eff}_{i,t-j} \oplus \sum_{j=1}^{2} \pi\text{-Eff}_{i,t-j}\right] \\ & + \sum_{j=1}^{2} \text{E/TA}_{i,t-j} + \text{TA}_{\text{i,t}} + \text{ID}_{\text{i,t}} + \text{MRISK}_{\text{i,t}} + \text{GDP}_{\text{t}} \\ & + \text{INTRATE}_{\text{t}} + \text{UNEMP}_{\text{t}} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

$$\text{X-Eff}_{i,t} = \left[\sum_{j=1}^{2} LLP_{i,t-j} \vee \sum_{j=1}^{2} LIQ_{i,t-j}\right] + \sum_{j=1}^{2} \text{X-Eff}_{i,t-j} + \sum_{j=1}^{2} \text{E/TA}_{i,t-j} + \text{TA}_{\text{i,t}} + \text{ID}_{\text{i,t}} + \text{MRISK}_{\text{i,t}} + \text{GDP}_{\text{t}} + \text{INTRATE}_{\text{t}} + \text{UNEMP}_{\text{t}} + \varepsilon_{i,t} \tag{8}$$

$$\pi\text{-Eff}_{\text{i,t}} = \left[\sum_{j=1}^{2} LLP_{i,t-j} \vee \sum_{j=1}^{2} LIQ_{i,t-j}\right] + \sum_{j=1}^{2} \pi\text{-Eff}_{i,t-j} + \sum_{j=1}^{2} \text{E/TA}_{i,t-j} + \text{TA}_{\text{i,t}} + \text{ID}_{\text{i,t}} + \text{MRISK}_{\text{i,t}} + \text{GDP}_{\text{t}} + \text{INTRATE}_{\text{t}} + \text{UNEMP}_{\text{t}} + \varepsilon_{i,t} \tag{9}$$

$$\text{E/TA}_{\text{i,t}} = \left[\sum_{j=1}^{2} LLP_{i,t-j} \vee \sum_{j=1}^{2} LIQ_{i,t-j}\right] + \left[\sum_{j=1}^{2} \text{X-Eff}_{i,t-j} \oplus \sum_{j=1}^{2} \pi\text{-Eff}_{i,t-j}\right] + \sum_{j=1}^{2} \text{E/TA}_{i,t-j} + \text{TA}_{\text{i,t}} + \text{ID}_{\text{i,t}} + \text{MRISK}_{\text{i,t}} + \text{GDP}_{\text{t}} + \text{INTRATE}_{\text{t}} + \text{UNEMP}_{\text{t}} + \varepsilon_{i,t} \tag{10}$$

i and *t* are defined as before. $LLP_{i,t}$ is loan loss provision scaled by total loans, $LIQ_{i,t}$ is liquid assets scaled by total demand deposits, *X-Eff* and *π-Eff* are cost- and profit-efficiency measured in the first step, and E/TA is equity scaled by total assets. In addition to these variables, we add four types of control variables: TA is the natural logarithm of total assets, ID is net non-interest income scaled by net operating income, $MRISK$ is the sum of securities traded on stock markets scaled by earning assets, while GDP, $INTRATE$ and $UNEMP$ are defined as for equation (3).

Since we estimate a dynamic panel model with added lags of the dependent variable as independent variables, the estimation via OLS is problematic. Lagged dependent variables are correlated with the error term due to unobserved heterogeneity, which causes upward biases of the relevant coefficients. To address this issue, we could eliminate the firm effects (also called fixed effects) causing the error term correlation by employing within estimations. The prevailing disadvantage of this approach is that correlation is removed only in cases when $T \rightarrow \infty$; otherwise, the coefficients are downward biased. Due to this problem, Arellano and Bond (1991) develop the difference generalized method of moments (GMM), which uses the first-differenced equation to eliminate the fixed effect and utilize all available lagged dependent variables as instruments to avoid correlation with the error term. Although the difference GMM is more appropriate, it still causes problems with estimations in micro panel datasets with volatile variables: First, a short sample period results in a small number of potential instruments to prevent correlation with the error term. Second, if the dependent variable is volatile, the lagged differences used in the difference GMM are weak instruments, and the resulting coefficients are downward biased.

For this reason, we use the two-step system GMM estimator based on Arellano and Bover (1995) and Blundell and Bond (1998).[6] System GMM extends the difference GMM by adding equations in levels as potential moment restrictions. Since it has been shown that the resulting standard errors in system GMM are downward biased in small T panels, we apply the standard error correction for finite-sample panels developed by Windmeijer (2005).

We also report results of the Arellano-Bond test for autocorrelation in levels and equations (AR(1) and AR(2)) as well as the Hansen test. AR(1) tests for autocorrelation in differenced error terms to control for fixed effects. $\Delta\varepsilon_{i,t}$ should correlate with $\Delta\varepsilon_{i,t-1}$ if fixed effects have been eliminated successfully since both differences share the component $\varepsilon_{i,t-1}$. AR(2) tests for the endogeneity of lags of the dependent variable. If the AR(2) test shows significance below 10%, the lags of the variable are endogenous and therefore bad instruments. The Hansen test for over-identifying restrictions tests the null hypothesis regarding whether employed instruments are – as a group – exogenous and thus good instruments. In contrast to the Sargan test, the Hansen test is robust to heteroscedasticity and autocorrelation but may be weakened if many instruments are used. Since we use a reasonable number of instruments, this limitation is applicable in our setting.

The literature in this field recommends the use of two lags (e.g. Williams, 2004; Casu and Girardone, 2009; Fiordelisi et al., 2011). Applying these two lags, we calculate the total effect of the lagged variables as the sum of their coefficients. Based on this total effect, we employ two different Wald tests to check for Granger causality. Wald test 1 represents for each lagged variable the joint test of the null

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[6] The system GMM estimator is estimated using the Stata command "xtabond2" written by Roodman (2009).

hypothesis that both lags are equal to zero and is distributed as chi-square (χ^2) with two degrees of freedom. This joint test operates as a panel test for Granger causality.[7] Wald test 2 represents for each lagged variable the test of the null hypothesis that the sum of both lags is equal to zero. If the null hypothesis in Wald test 2 is not rejected, the level of the dependent variable is influenced by the change in the lagged independent variable and not by its level.

2.4 Variables, Data and Descriptive Statistics

Due to data limitations, we follow Williams (2004) and use loan loss provision (LLP) as a proxy for credit risk. Regarding capital, we use the equity-to-assets ratio (E/TA), calculated as the book value of equity to total assets. This measure clearly reflects bank capital risk. We further use a broader measure of bank capital as a robustness test. This alternative measure of bank capital (E_A/TA) includes preferred shares and hybrid capital and subordinated liabilities in addition to the standard measure of bank capital. We use this measure to gain a deeper understanding of how additional capital reserves built by banks are related to the relevant variables of investigation. For the investigation of bank liquidity risk, we introduce a measure of bank liquidity risk (LIQ) applied by Radić (2015). This measure of liquidity contrasts bank claims due on demand (cash assets reserves, overnight debt due, trading assets, inventory on hands, money held in trust) with overnight liabilities. Concerning our risk measures, we are consequently able to draw a comprehensive bank risk profile by applying measures for credit risk (LLP), capital risk (E/TA, E_A/TA) and liquidity risk (LIQ).

We use cost efficiency and profit efficiency as measures for bank efficiency since these measures reflect different managerial abilities, i.e., the abilities to manage costs and profits. Thus, we assume that these measures may have different links to our three risk measures.

We further control for following factors that may have an impact on the ties of efficiency, risk and capital: overall market risk ($MRISK$) controls for differences in the focus on market-related assets (debt instruments issued for public-sector

[7] X positively Granger-causes y if $x_{t-1}$and x_{t-2} are independent variables and are both statistically significant on dependent variable y (Granger, 1969).

institutions and bills of exchange, bonds and other fixed-interest securities, shares and other non-fixed-interest securities). We consider this measure important since our data cover the financial crisis and the euro sovereign debt crisis, which led to substantial shifts on banks' balance sheets. The same applies to our measure of income diversification (ID), which aims to capture differences in business focus across banks by contrasting their commission margin, trade margin and other earnings assets to their net operating income. The natural logarithm of total assets (TA) controls for differences in bank asset size. Finally, variables for GDP growth (GDP), interest rate ($INTRATE$) and unemployment rate ($UNEMP$) are included to capture the heterogeneity of the macroeconomic development across years.[8]

We use hand collected annual balance sheet and income statement data of 328 cooperative banks from Bavaria between 2007 and 2014. After excluding mergers and banks with insufficient data, our final sample consists of 205 Cooperative banks. Table 2.1 summarizes the data set modifications.

Table 2.1
Sample Selection

Initial sample of Bavarian cooperative banks with balance sheet and income statement data from 2007 to 2014 (Source: German "Bundesanzeiger")	328 banks
Exclusion of banks which were actively or passively participating in a merger between 2007 and 2014	-121 banks
Exclusion of banks with predominantly insufficient data	-2 banks
Final Sample	205 banks
	1640 Observations

Cooperative banks are retail-oriented banks that differ to some extent from commercial banks in terms of, e.g., the nature of non-interest income. Thus, they focus on commission income (fees) rather than on commercial paper or financial derivatives as a form of non-interest income. At the same time, cooperative banks can be assigned to the group of small banks, such as community banks and credit unions. These banks play an important role in many developed economies (the US, Australia and several countries in Europe) as they rely on relationship lending with a strong focus on local development. Based on their different business model, these banks exhibit a different risk profile than commercial banks. This is what makes

[8] See Appendix 2.A for detailed information concerning the variable description.

these banks of particular interest as their competitive environment differs largely from commercial banks.[9]

Table 2.2 contains summary statistics of the variables of interest. While the mean cost efficiency is approximately 96.30%, the average profit efficiency is slightly lower (95.83%). Loan loss provision ranges from -5.28% to 6.27%, which indicates that some banks performed appreciations (negative values) in certain years. Liquidity shows that at least one bank almost ran out of liquidity in a certain year (0.34%). The equity-to-assets ratio reveals that some banks hold large bank capital (maximum of 30.45%), whereas others hold low bank capital (minimum of 3.26%). While some banks do not participate in market-related investments (0.00%), others are heavily invested in these assets (60.53%). Total assets range from 21 million euro to 4.7 billion euro, indicating that our sample comprises small and medium-sized banks.

Table 2.2
Descriptive statistics of relevant regression variables

	Mean	Median	Std. Dev.	Min	Max
$X - Eff.$	0.963	0.974	0.035	0.446	0.996
$\pi - Eff.$	0.958	0.968	0.043	0.000	0.990
LLP	0.002	0.003	0.007	-0.053	0.063
LIQ	0.189	0.159	0.128	0.003	1.409
E/TA	0.071	0.068	0.021	0.033	0.305
E_A/TA	0.073	0.070	0.021	0.037	0.305
$MRISK$	0.295	0.296	0.114	0.000	0.605
TA	5.554	5.654	1.071	-2.551	8.459
ID	0.180	0.173	0.060	-0.101	0.549

Table 2.3 exhibits the development of the variables of interest over time. Liquidity dries up from over 27 percent in 2007 to less than 12 percent in 2014. The influence of the financial crisis during the period 2007 – 2008 and the euro sovereign debt crisis starting around 2010 is appreciable by the double U-shaped form of profit efficiency scores. E/TA recovered from 6.32% and 6.18% during the financial crisis in 2007 – 2008 to 8.21% in 2014. The numbers of our measure of market risk ($MRISK$) are particularly interesting, as they show that cooperative banks shifted

[9] See Appendix 2.B for the correlation matrix of relevant variables.

their balance sheet towards these positions (especially after the period of the financial crisis). TA indicates that cooperative banks are growing in asset size, on average. ID shows that the average bank increases revenues from non-interest activities. The number increase from 17.65% in 2007 to 19.89% in 2014

Table 2.3
Development of mean values of relevant regression variables

	LLP	LIQ	$X-Eff$	$\pi-Eff$	E/TA	E_A/TA	$MRISK$	TA	ID
2007	0.0060	0.2705	0.9740	0.9694	0.0632	0.0665	0.2415	5.3979	0.1765
2008	0.0060	0.2663	0.9721	0.8783	0.0618	0.0646	0.2501	5.4527	0.1658
2009	0.0043	0.2295	0.9783	0.9812	0.0630	0.0658	0.3030	5.4985	0.1607
2010	0.0057	0.1813	0.9627	0.9829	0.0661	0.0688	0.3096	5.5379	0.1749
2011	0.0045	0.1671	0.9576	0.9661	0.0689	0.0714	0.2991	5.5741	0.1796
2012	-0.0028	0.1589	0.9561	0.9576	0.0764	0.0787	0.3197	5.6127	0.1860
2013	-0.0027	0.1263	0.9596	0.9626	0.0841	0.0861	0.3208	5.6412	0.1970
2014	-0.0016	0.1137	0.9433	0.9670	0.0821	0.0837	0.3124	5.7195	0.1989
Total	0.0024	0.1891	0.9630	0.9583	0.0707	0.0732	0.2950	5.5543	0.1799

2.5 Empirical Results

2.5.1 Cost-efficiency Estimations

Following Fiordelisi et al. (2011), we estimate credit risk (LLP), cost efficiency ($X - Eff$)[10] and bank capital (E/TA). In addition, we re-estimate these regressions by replacing LLP with liquidity (LIQ) to investigate all links concerning bank liquidity risk (Table 2.4, columns 4-6). Finally, we estimate a comprehensive bank risk model by including LIQ, LLP and capital risk (E/TA) in the same estimation (Table 2.4, columns 7-10).

Concerning the "bad management" hypothesis we do not measure any effect of cost-efficiency on loan loss provision. However, the results in Table 2.4 suggest that cost efficiency positively Granger-causes liquidity risk (column 4).

With respect to E/TA, our results show – as expected – evidence against the "moral hazard" hypothesis (column 1 and 7). Specifically, we measure a positive relation between bank capital and loan loss provision, suggesting that banks with low bank capital are able to limit their exposure to problem loans in following periods. Thus, limited liability and deposit insurance do not seem to drive cooperative banks to take on more risk.

In terms of our cost-efficiency regressions (columns 2 and 9), we identify a negative relationship between loan loss provision and estimated cost efficiency. Thus, higher shares of problem loans Granger-cause a decrease in cost efficiency, which confirms the "bad luck" hypothesis. The financial crisis as well as the euro sovereign debt crisis may have led to an increasing share of problem loans, which subsequently led to decreasing cost efficiency for cooperative banks.

We also show that there is a negative relationship between loan loss provision and bank capital in columns 3 and 10. This result is not surprising, as loan loss provision burns bank capital.

The results also indicate that decreases in bank capital Granger-cause increases in cost efficiency (column 2 and 5). That is, banks that suffer from decreasing bank capital are inclined to manage their costs in following periods. This finding is

[10] See Appendix 2.C for detailed information about cost-efficiency estimations.

contrary to Fiordelisi et al. (2011) and confirms our results that counter the “moral hazard” hypothesis. Thus, cooperative banks (as opposed to commercial banks) do not suffer from inappropriate incentives when capital declines.

Moreover, we identify a positive impact of liquidity on bank capital in our liquidity model and our comprehensive risk model (columns 6 and 10). Thus, increases in liquidity precede increases in bank capital. As risk preferences are often reflected in the amount of both bank capital and liquidity, this finding is economically reasonable.

We also find evidence of a negative relationship between total assets (TA) and LIQ (columns 4 and 8). That implies that large banks tend to hold less liquidity than small banks. At the same time, the results show that market risk is negatively related to liquidity. Finally, diversified banks (in terms of revenue diversification) tend to hold more bank capital.

Turning to Table 2.5, we employ a broader measure of equity, E_A/TA, which adds preferred shares and hybrid capital and subordinated liabilities to the book value of equity capital.

Again – in column 1 and 7 – we identify a positive impact of bank capital on loan loss provision (which confirms our findings that counter the “moral hazard” hypothesis). We further measure significant results concerning the relationship between loan loss provision and cost efficiency (column 2 and 9). This indicates that economic distortions affect a banks cost-efficiency negatively. Hence, this finding confirms the “bad luck” hypothesis.

Furthermore, we again measure that cost-efficiency positively Granger-causes liquidity risk. This may support the assumption that a banks’ management that is not able to handle costs faces issues taking appropriate actions concerning term transformation and hence the level of liquidity. Regarding this context, we can confirm the “bad management” hypothesis.

Table 2.4

Regression results for the relationships among risk, cost efficiency and capital of sample banks using Granger-causality technique

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Y = LLP	Y = X-Eff$_t$	Y = E/TA$_t$	Y = LIQ	Y = X-Eff$_t$	Y = E/TA$_t$	Y = LLP	Y = LIQ	Y =X-Eff$_t$	Y = E/TA$_t$
LLP$_{t-1}$	-0.517***	-0.034	-1.074**				-0.456***	-0.444	0.065	-0.406***
	(0.147)	(0.596)	(0.534)				(0.133)	(1.111)	(0.665)	(0.124)
LLP$_{t-2}$	-0.379***	-0.939**	0.683*				-0.360***	-1.068**	-0.931**	0.163**
	(0.076)	(0.460)	(0.388)				(0.103)	(0.465)	(0.424)	(0.067)
LLP$_{Wald\ 1}$	-0.896***	-0.973*	-0.391***				-0.816***	-1.512*	-0.866**	-0.243***
LLP$_{Wald\ 2}$	-0.896***	-0.973***	-0.391				-0.816***	-1.512	-0.866	-0.243*
LIQ$_{t-1}$				0.416***	0.065	0.114***	-0.002	0.370***	0.036	0.041***
				(0.084)	(0.061)	(0.040)	(0.010)	(0.083)	(0.042)	(0.012)
LIQ$_{-2}$				0.051	-0.125***	0.020	0.014*	0.125**	-0.003	-0.022**
				(0.040)	(0.048)	(0.017)	(0.008)	(0.053)	(0.022)	(0.010)
LIQ$_{Wald\ 1}$				0.467***	-0.060**	0.134**	0.012	0.495***	0.033	0.019***
LIQ$_{Wald\ 2}$				0.467***	-0.060	0.134***	0.012	0.495***	0.033	0.019*
X-Eff$_{t-1}$	-0.008	0.588***	-0.067	0.666**	0.757***	0.193**	-0.033*	0.423*	0.464**	0.074*
	(0.022)	(0.185)	(0.147)	(0.264)	(0.202)	(0.093)	(0.020)	(0.253)	(0.182)	(0.039)
X-Eff$_{t-2}$	0.041*	-0.242	-0.260	-0.238	0.008	-0.174	0.020	-0.195	-0.279	-0.054
	(0.024)	(0.265)	(0.166)	(0.240)	(0.232)	(0.116)	(0.020)	(0.137)	(0.241)	(0.034)
X-Eff$_{Wald\ 1}$	0.033	0.346***	-0.327	0.428**	0.765***	0.019*	-0.013	0.228	0.185**	0.020
X-Eff$_{Wald\ 2}$	0.033	0.346**	-0.327	0.428*	0.765***	0.019	-0.013	0.228	0.185	0.020
E/TA$_{t-1}$	-0.445***	1.305*	-0.273	-1.828	1.294**	0.897***	-0.304*	-3.483**	1.091	0.663***
	(0.170)	(0.687)	(0.831)	(1.371)	(0.593)	(0.311)	(0.157)	(1.646)	(0.823)	(0.218)
E/TA$_{t-2}$	0.515***	-2.030***	1.392*	2.530*	-1.343**	-0.457	0.372**	3.750**	-1.720*	0.322
	(0.170)	(0.722)	(0.794)	(1.314)	(0.648)	(0.373)	(0.150)	(1.637)	(0.892)	(0.218)
E/TA$_{Wald\ 1}$	0.070***	-0.725**	1.119***	0.702**	-0.049*	0.440***	0.068**	0.267*	-0.629	0.985***
E/TA$_{Wald\ 2}$	0.070	-0.725	1.119***	0.702*	-0.049	0.440*	0.068	0.267	-0.629	0.985***
MRISK	-0.002	0.063**	0.061	-0.267***	-0.001	0.091**	-0.010	-0.113*	0.085**	0.016**
	(0.009)	(0.028)	(0.042)	(0.070)	(0.042)	(0.041)	(0.009)	(0.064)	(0.039)	(0.008)
TA	-0.000	-0.004	0.009	-0.019**	-0.003	0.003	0.000*	-0.020***	-0.004	0.002**
	(0.001)	(0.004)	(0.008)	(0.009)	(0.005)	(0.004)	(0.001)	(0.007)	(0.004)	(0.001)
ID	-0.019	0.056	0.121**	-0.288**	-0.021	0.290***	-0.026***	-0.146	0.023	0.031**
	(0.016)	(0.077)	(0.055)	(0.146)	(0.094)	(0.082)	(0.009)	(0.148)	(0.082)	(0.015)
GDP	0.059***	-0.194***	0.035	-0.152*	-0.143***	-0.043**	0.058***	-0.151*	-0.170***	-0.002
	(0.006)	(0.031)	(0.030)	(0.091)	(0.046)	(0.020)	(0.007)	(0.087)	(0.045)	(0.009)
INTRATE	0.638***	1.349	1.452**	2.961**	1.142	0.666*	0.633***	2.750**	1.188	0.734***
	(0.161)	(0.842)	(0.633)	(1.310)	(0.750)	(0.386)	(0.127)	(1.155)	(0.854)	(0.182)
UNEMP	0.218***	0.197	-0.197	-1.107**	0.322	-0.753***	0.202***	-1.091*	0.151	-0.380***

	(0.040)	(0.228)	(0.162)	(0.553)	(0.315)	(0.219)	(0.057)	(0.664)	(0.281)	(0.073)
CONST	-0.045	0.647***	0.224	-0.099	0.228	-0.058	-0.002	0.059	0.794***	-0.023
	(0.029)	(0.228)	(0.1778)	(0.233)	(0.168)	(0.115)	(0.025)	(0.196)	(0.250)	(0.037)
Observations	1190	1182	1190	1184	1183	1191	1190	1183	1182	1190
Instruments	83	63	28	103	52	38	87	123	74	120
Hansen test, 2nd step	76.23	40.17	11.80	91.35	26.76	24.49	65.85	98.28	47.93	109.75
AB test AR (1)	-3.39***	-2.85***	-3.76***	-4.02***	-2.76***	-2.95***	-3.64***	-3.90***	-3.04***	-4.29***
AB test AR (2)	0.81	0.64	0.16	0.57	0.03	0.86	0.61	0.13	0.78	0.89

We use two-step system GMM estimations with Windmeijer's (2005) corrected standard errors. Wald 1 coefficients capture joint test of the null hypothesis that both lags are equal to zero and are distributed as chi-square (χ^2) with two degrees of freedom. Wald 2 coefficients represent for each lagged variable the test of the null hypothesis that the sum of both lags is equal to zero. Statistical significance (10%, 5% and 1%) rejects the null hypothesis and confirms that x Granger-causes y. The Hansen test of over-identifying restrictions for GMM estimations tests whether the null hypothesis (applied instruments are not correlated with the error term) is valid. The Arellano-Bond (AB) test for serial correlation tests whether the null hypothesis (errors in the first-difference regression do not suffer from second-order serial correlation) is valid.

Table 2.5
Robustness test: Testing the relationships among risk, cost efficiency and capital
(using equity capital plus supplemental capital items to total assets as a measure of bank capital) of
sample banks using Granger-causality technique

	(1) Y = LLP	(2) Y = X-Eff$_t$	(3) Y = E$_A$/TA$_t$	(4) Y = LIQ	(5) Y = X-Eff$_t$	(6) Y = E$_A$/TA$_t$	(7) Y = LLP	(8) Y = LIQ	(9) Y =X-Eff$_t$	(10) Y = E$_A$/TA$_t$
LLP$_{t-1}$	-0.643***	0.539	-0.379*				-0.195**	-0.436	0.274	-0.376**
	(0.210)	(0.533)	(0.211)				(0.084)	-1.086	(0.575)	(0.159)
LLP$_{t-2}$	-0.504***	-0.596*	0.901***				-0.272***	-1.059*	-0.745**	0.363***
	(0.112)	(0.313)	(0.172)				(0.075)	(0.569)	(0.334)	(0.113)
LLP$_{Wald\ 1}$	-1.147***	-0.057*	0.522***				-0.467***	-1.495	-0.471**	-0.013***
LLP$_{Wald\ 2}$	-1.147***	-0.057	0.522				-0.467***	-1.495	-0.471	-0.013
LIQ$_{t-1}$				0.344***	0.048*	0.112***	0.001	0.306**	0.008	0.045***
				(0.074)	(0.028)	(0.033)	(0.005)	(0.125)	(0.022)	(0.017)
LIQ$_{t-2}$				0.161*	-0.064**	-0.051**	0.001	0.075	-0.007	-0.018**
				(0.087)	(0.029)	(0.026)	(0.003)	(0.083)	(0.016)	(0.009)
LIQ$_{Wald\ 1}$				0.505***	-0.016**	0.061***	0.002	0.381***	0.001	0.027**
LIQ$_{Wald\ 2}$				0.505***	-0.016	0.061*	0.002	0.381***	0.001	0.027*
X-Eff$_{t-1}$	0.039	0.415*	-0.053	0.066	0.642***	0.009	-0.003	0.500**	0.546***	0.022
	(0.028)	(0.227)	(0.084)	(0.283)	(0.133)	(0.115)	(0.017)	(0.235)	(0.220)	(0.039)
X-Eff$_{t-2}$	0.000	-0.133	-0.138	0.602**	0.019	-0.199	0.014	-0.404	-0.144	-0.046
	(0.018)	(0.229)	(0.093)	(0.260)	(0.077)	(0.125)	(0.010)	(0.353)	(0.202)	(0.033
X-Eff$_{Wald\ 1}$	0.039	0.282	-0.191	0.668**	0.661***	-0.190	0.011	0.096*	0.402**	-0.024
X-Eff$_{tWald\ 2}$	0.039	0.282	-0.191	0.668**	0.661***	-0.190	0.011	0.096	0.402	-0.024
E$_A$/TA$_{t-1}$	-0.357	1.625**	0.277	-2.210**	1.050***	1.058***	-0.030	-3.172	1.399**	0.639***
	(0.247)	(0.732)	(0.359)	(0.942)	(0.331)	(0.308)	(0.070)	-2.107	(0.575)	(0.243)
E$_A$/TA$_{t-2}$	0.517**	-2.044***	0.718**	2.649***	-1.156***	-0.297	0.124*	3.661*	-1.864***	0.352
	(0.234)	(0.719)	(0.352)	(0.952)	(0.401)	(0.331)	(0.071)	-2.147	(0.552)	(0.250)
E$_A$/TA$_{Wald\ 1}$	0.160**	-0.419***	0.995***	0.439**	-0.106***	0.761***	0.094*	0.489	-0.465***	0.991***
E$_A$/TA$_{Wald\ 2}$	0.160*	-0.419*	0.995***	0.439	-0.106	0.761***	0.094**	0.489	-0.465**	0.991
MRISK	-0.002	0.088**	-0.001	-0.169***	0.012	0.030	0.010	-0.077	0.070**	0.019*
	(0.011)	(0.042)	(0.017)	(0.057)	(0.019)	(0.037)	(0.006)	(0.091)	(0.035)	(0.010)
TA	-0.000	0.002	0.004*	-0.017**	-0.001	0.006**	0.001	-0.025**	-0.002	0.004***
	(0.001)	(0.004)	(0.002)	(0.008)	(0.002)	(0.003)	(0.001)	(0.011)	(0.002)	(0.001)
ID	0.004	0.045	0.124***	-0.069	-0.022	0.136***	0.012	-0.292	0.004	0.033*
	(0.019)	(0.093)	(0.038)	(0.104)	(0.055)	(0.050)	(0.013)	(0.267)	(0.072)	(0.017)
GDP	0.060***	-0.172***	0.012	-0.284***	-0.170***	0.016	0.055***	-0.140	-0.202***	0.004
	(0.008)	(0.038)	(0.016)	(0.101)	(0.030)	(0.022)	(0.005)	(0.115)	(0.035)	(0.012)
INTRATE	1.027***	1.149*	0.512	1.386	1.134**	0.947***	0.592***	3.672**	1.227**	0.629***
	(0.184)	(0.691)	(0.325)	-1.085	(0.503)	(0.341)	(0.127)	-1.480	(0.564)	(0.176)
UNEMP	0.236***	0.460*	-0.207*	-0.876	0.092	-0.353**	0.318***	-0.739	0.212	-0.341***

	(0.062)	(0.259)	(0.113	(0.583)	(0.218)	(0.179)	(0.037)	(0.618)	(0.255)	(0.098)
CONST	-0.064**	0.631**	0.151	-0.406	0.329***	0.137	-0.048**	0.210	0.575**	0.002
	(0.027)	(0.284)	(0.109)	(0.275)	(0.106)	(0.117)	(0.021)	(0.369)	(0.251)	(0.043)
Observations	1190	1182	1190	1184	1183	1191	1190	1183	1182	1190
Instruments	69	70	46	105	109	43	143	81	95	106
Hansen test, 2nd step	52.57	47.33	25.68	89.35	93.92	30.03	134.53	65.70	69.16	99.02
AB test AR (1)	-2.92***	-2.79***	-4.26***	-3.61***	-3.88***	-2.87***	-4.19***	-2.97***	-3.02***	-4.42***
AB test AR (2)	0.82	0.05	0.38	-0.59	-0.37	0.83	1.03**	0.13	0.25	0.87

We use two-step system GMM estimations with Windmeijer's (2005) corrected standard errors. Wald 1 coefficients capture the joint test of the null hypothesis that both lags are equal to zero and are distributed as chi-square (χ^2) with two degrees of freedom. Wald 2 coefficients represent for each lagged variable the test of the null hypothesis that the sum of both lags is equal to zero. Statistical significance (10%, 5% and 1%) rejects the null hypothesis and confirms that x Granger-causes y. The Hansen test of over-identifying restrictions for GMM estimations tests whether the null hypothesis (applied instruments are not correlated with the error term) is valid. The Arellano-Bond (AB) test for serial correlation tests whether the null hypothesis (errors in the first-difference regression do not suffer from second-order serial correlation) is valid.

2.5.2 Profit-efficiency Estimations

Table 2.6 shows all regressions related to profit efficiency[11]. We find evidence for a negative impact of profit efficiency on loan loss provision (columns 1 and 7). Thus, we can confirm the "bad management" hypothesis when we use profit efficiency as a measure of bank efficiency: Banks that are not able to manage their earnings perceive higher credit risk in following periods. At the same time, we can confirm the "bad management" hypothesis when we use our measure of liquidity as a measure of bank risk (column 4 and 8). Similar to our cost-efficiency estimations, the results for credit risk estimations show strong evidence of a positive impact of bank capital on loan loss provision (column 1 and 7). Again, this contradicts the common perception of moral hazard behaviour in banks. Results also show a negative impact of loan loss provision on profit efficiency (columns 2 and 9) yielding a bidirectional relationship between these two measures. Thus, we can confirm the "bad luck" hypothesis for our cost and profit-efficiency estimations. We further identify that banks that are more efficient become better-capitalized (column 3, 6 and 10) and, at the same time, higher ratios of bank capital appear to have a positive impact on bank efficiency.

Similar to the cost-efficiency estimations in table 2.4, we identify a positive impact of market risk on bank capital. In addition, large banks tend to hold a higher level of bank capital and a lower level of liquidity. Similar to the cost-efficiency estimations in table 2.4, we find that diversified banks appear to hold a higher level of bank capital.

[11] See Appendix 2.D for detailed information about profit-efficiency estimations.

Table 2.6
Testing the relationships among risk, profit efficiency and capital of German cooperative banks using Granger-causality technique

	(1) Y = LLP	Model (2) Y = π-Eff$_t$	(3) Y = E/TA$_t$	(4) Y = LIQ	(5) Y = π-Eff$_t$	(6) Y = E/TA$_t$	(7) Y = LLP	(8) Y = LIQ	(9) Y = π-Eff$_t$	(10) Y = E/TA$_t$
LLP$_{t-1}$	-0.394***	-0.234**	-0.439***				-0.038	-0.449	-0.169*	-0.217**
	(0.147)	(0.115)	(0.120)				(0.085)	(0.983)	(0.098)	(0.108)
LLP$_{t-2}$	-0.304***	-0.176*	0.091				0.086	-0.932*	-0.285***	0.136**
	(0.113)	(0.103)	(0.070)				(0.056)	(0.504)	(0.098)	(0.059)
LLP$_{Wald\ 1}$	-0.698***	-0.410*	-0.348***				0.048	-1.381	-0.454**	-0.081**
LLP$_{Wald\ 2}$	-0.698***	-0.410*	-0.348**				0.048	-1.381	-0.454***	-0.081
LIQ$_{t-1}$				0.542***	-0.002	0.015**	-0.016*	0.412***	-0.008	0.013*
				(0.147)	(.022)	(0.007)	(0.008)	(0.103)	(0.008)	(0.007)
LIQ$_{t-2}$				0.168*	-0.039*	-0.003	0.006	0.138**	0.005	-0.003
				(0.095)	(0.022)	(0.003)	(0.006)	(0.055)	(0.005)	(0.003)
LIQ$_{Wald\ 1}$				0.710***	-0.041	0.012*	-0.010	0.550***	-0.003	0.010
LIQ$_{Wald\ 2}$				0.710***	-0.041	0.012**	-0.010	0.550***	-0.003	0.010
π-Eff$_{t-1}$	-0.106***	0.001	0.189***	0.967**	0.055	0.129***	-0.066*	0.536*	-0.032	0.127**
	(0.037)	(0.047)	(0.073)	(0.477)	(0.102)	(0.038)	(0.036)	(0.299)	(0.032)	(0.051)
π-Eff$_{t-2}$	-0.010**	0.081**	-0.071**	0.632*	0.159***	-0.014*	0.024	0.073	0.016	-0.010
	(0.004)	(0.040)	(0.031)	(0.333)	(0.062)	(0.008)	(0.023)	(0.115)	(0.018)	(0.006)
π-Eff$_{Wald\ 1}$	-0.116***	0.082**	0.118***	1.599*	0.214***	0.115***	-0.042***	0.609	-0.016	0.117***
π-Eff$_{Wald\ 2}$	-0.116***	0.082	0.118	1.599**	0.214	0.115***	-0.042	0.609*	-0.016	0.117**
E/TA$_{t-1}$	-0.219	-0.085	0.680***	-3.171**	0.317**	1.071***	0.214**	-3.039**	0.090	0.773***
	(0.204)	(0.190)	(0.206)	-1.368	(0.145)	(0.145)	(0.096)	-1.404	(0.093)	(0.188)
E/TA$_{t-2}$	0.344*	0.296*	0.398*	3.012**	-0.141	-0.138	-0.059*	3.232**	0.033	0.238
	(0.193)	(0.162)	(0.216)	-1.333	(0.152)	(0.151)	(0.109)	-1.443	(0.090)	(0.184)
E/TA$_{Wald\ 1}$	0.125**	0.211**	1.078***	-0.159*	0.176*	0.933*	0.155***	0.193*	0.123	1.011***
E/TA$_{Wald\ 2}$	0.125*	0.211*	1.078***	-0.159	0.176	0.933**	0.155**	0.193	0.123*	1.011***
MRISK	0.017**	-0.003	0.014*	-0.104*	-0.008	0.013*	-0.001	-0.070	0.014*	0.026***
	(0.008)	(0.007)	(0.008)	(0.060)	(0.015)	(0.007)	(0.007)	(0.048)	(0.008)	(0.008)
TA	0.001	-0.000	0.002*	-0.016***	-0.002	0.002**	-0.000	-0.010*	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.006)	(0.002)	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)
ID	0.020	-0.009	0.064*	-0.277	0.007	0.037***	-0.025**	-0.117	-0.006	0.037*
	(0.162)	(0.012)	(0.038)	(0.204)	(0.022)	(0.012)	(0.012)	(0.106)	(0.013)	(0.021)
GDP	0.146***	0.152***	-0.243***	-0.555*	0.177***	-0.149***	0.130***	-0.600*	0.119***	-0.136***
	(0.0351)	(0.035)	(0.060)	(0.332)	(0.056)	(0.039)	(0.023)	(0.314)	(0.025)	(0.051)
INTRATE	0.993***	-1.528***	1.183***	-6.092*	-2.264***	0.483***	0.242	1.165	-0.973***	0.523***
	(0.156)	(0.464)	(0.360)	-3.392	(0.686)	(0.134)	(0.275)	-1.613	(0.224)	(0.160)
UNEMP	0.147**	1.683***	-0.359*	2.498	2.358***	-0.172***	0.403***	0.042	1.383***	-0.165*
	(0.061)	(0.224)	(0.197)	-1.911	(0.403)	(0.066)	(0.140)	(0.832)	(0.108)	(0.096)
CONST	0.076*	0.793***	-0.125	-1.404*	0.649***	-0.117***	0.012	-0.441	0.902***	-0.125**

	(0.040)	(0.080)	(0.094)	(0.789)	(0.170)	(0.039)	(0.061)	(0.349)	(0.051)	(0.055)
Observations	1190	1182	1190	1184	1183	1191	1190	1183	1182	1190
Instruments	80	77	83	78	29	126	91	106	139	129
Hansen test, 2nd step	67.00	65.77	72.56	50.01	12.31	131.60	81.01	81.65	130.37	119.92
AB test AR (1)	-3.29***	-2.04**	-2.61***	-2.58***	-2.05**	-4.14***	-3.93***	-3.50***	-1.85*	-3.50***
AB test AR (2)	0.68	-1.88*	0.35	-0.20	-1.50	-0.89	-0.89	-0.05	-1.92**	-0.48

We use two-step system GMM estimations with Windmeijer's (2005) corrected standard errors. Wald 1 coefficients capture the joint test of the null hypothesis that both lags are equal to zero and are distributed as chi-square (χ^2) with two degrees of freedom. Wald 2 coefficients represent for each lagged variable the test of the null hypothesis that the sum of both lags is equal to zero. Statistical significance (10%, 5% and 1%) rejects the null hypothesis and confirms that x Granger-causes y. The Hansen test of over-identifying restrictions for GMM estimations tests whether the null hypothesis (applied instruments are not correlated with the error term) is valid. The Arellano-Bond (AB) test for serial correlation tests whether the null hypothesis (errors in the first-difference regression do not suffer from second-order serial correlation) is valid.

Table 2.7
Robustness test: Testing the relationships among risk, profit efficiency and capital (using equity capital plus supplemental capital items to total assets as a measure of bank capital) of German cooperative banks using Granger-causality technique

	(1) Y = LLP	(2) Y = π-Eff$_t$	(3) Y = E_A/TA_t	(4) Y = LIQ	(5) Y = π-Eff$_t$	(6) Y = E_A/TA_t	(7) Y = LLP	(8) Y = LIQ	(9) Y = π-Eff$_t$	(10) Y = E_A/TA_t
LLP_{t-1}	0.432*	-0.184*	-0.496***				0.012	-0.400	-0.141*	-0.361***
	(0.242)	(0.101)	(0.122)				(0.112)	-1.201	(0.085)	(0.121)
LLP_{t-2}	0.268	-0.193**	0.114*				0.042	-2.617**	-0.153*	0.097
	(0.256)	(0.099)	(0.066)				(0.046)	-1.269	(0.079)	(0.066)
$LLP_{Wald\ 1}$	0.700	-0.377**	-0.382***				0.054	-3.017	-0.294*	-0.264***
$LLP_{Wald\ 2}$	0.700*	-0.377**	-0.382***				0.054	-3.017	-0.294**	-0.264*
LIQ_{t-1}				0.358***	-0.011*	0.022*	-0.006	0.432***	-0.011	0.011*
				(0.122)	(0.006)	(0.011)	(0.006)	(0.106)	(0.007)	(0.006)
LIQ_{t-2}				0.111*	-0.001	-0.001	0.004	0.122	0.005	-0.005
				(0.064)	(0.006)	(0.008)	(0.003)	(0.086)	(0.005)	(0.003)
$LIQ_{Wald\ 1}$				0.469***	-0.012	0.021*	-0.002	0.554***	-0.006	0.006
$LIQ_{Wald\ 2}$				0.469***	-0.012*	0.021**	-0.002	0.554***	-0.006	0.006
π-Eff$_{t-1}$	-0.258***	0.001	0.125**	0.337	0.037	0.254***	-0.073**	0.564*	-0.010	0.112**
	(0.094)	(0.050)	(0.053)	(0.221)	(0.060)	(0.070)	(0.034)	(0.333)	(0.028)	(0.047)
π-Eff$_{t-2}$	0.016	0.096***	-0.076***	-0.112***	0.142***	-0.044	0.025*	-0.351	0.048**	-0.053***
	(0.036)	(0.034)	(0.025)	(0.039)	(0.034)	(0.032)	(0.014)	(0.275)	(0.024)	(0.020)
π-Eff$_{Wald\ 1}$	-0.242***	0.097***	0.049***	0.225***	0.179***	0.210***	-0.048***	0.213*	0.038**	0.059***
π-Eff$_{Wald\ 2}$	-0.242**	0.097	0.049	0.225	0.179**	0.210**	-0.048	0.213	0.038	0.059
E_A/TA_{t-1}	0.533*	0.030	0.699***	-1.347	0.117	1.326***	0.305**	-2.362	0.045	0.707***
	(0.303)	(0.123)	(0.174)	-1.040	(0.138)	(0.197)	(0.131)	-1.743	(0.094)	(0.173)
E_A/TA_{t-2}	-0.407	0.039	0.297*	2.301**	-0.056	-0.380*	-0.253**	2.908*	0.055	0.259
	(0.301)	(0.126)	(0.159)	-1.036	(0.120)	(0.216)	(0.126)	-1.683	(0.083)	(0.160)
$E_A/TA_{Wald\ 1}$	0.126*	0.069	0.996***	0.954**	0.061	0.946***	0.052**	0.546	0.100	0.966***
$E_A/TA_{Wald\ 2}$	0.126*	0.069	0.996***	0.954**	0.061	0.946***	0.052	0.546	0.100	0.966***
MRISK	-0.011	0.005	0.016**	-0.091	-0.002	0.034**	-0.006	-0.103*	0.012	0.017**
	(0.009)	(0.007)	(0.007)	(0.055)	(0.011)	(0.014)	(0.005)	(0.055)	(0.009)	(0.007)
TA	-0.001	-0.001	0.002**	-0.011	-0.002**	0.001*	-0.000	-0.008	-0.000	0.001*
	(0.001)	(0.001)	(0.001)	(0.008)	(0.001)	(0.001)	(0.000)	(0.009)	(0.001)	(0.001)
ID	-0.010	-0.007	0.032***	-0.279*	-0.019	0.068**	-0.021**	-0.173	-0.002	0.031**
	(0.029)	(0.009)	(0.012)	(0.150)	(0.016)	(0.028)	(0.010)	(0.109)	(0.012)	(0.014)
GDP	0.300***	0.161***	-0.196***	-0.567**	0.163***	-0.310***	0.138***	-1.021**	0.130***	-0.167***
	(0.080)	(0.039)	(0.050)	(0.231)	(0.040)	(0.058)	(0.031)	(0.401)	(0.021)	(0.046)
INTRATE	0.104	-1.812***	1.283***	3.361***	-2.438***	0.780**	0.149	6.078*	-1.404***	1.011***
	(0.432)	(0.336)	(0.268)	-1.170	(0.337)	(0.342)	(0.172)	-3.181	(0.254)	(0.228)
UNEMP	0.220	1.790***	-0.484***	-0.465	2.076***	-0.158	0.388***	-1.826	1.581***	-0.415***

	(0.223)	(0.200)	(0.159)	(0.609)	(0.220)	(0.237)	(0.094)	-1.491	(0.138)	(0.143)
CONST	0.213*	0.783***	-0.042	-0.063	0.708***	-0.224**	0.023	0.008	0.843***	-0.051
	(0.117)	(0.080)	(0.070)	(0.247)	(0.096)	(0.099)	(0.042)	(0.478)	(0.050)	(0.059)
Observations	1190	1182	1190	1184	1183	1191	1190	1183	1182	1190
Instruments	45	102	113	103	82	83	122	95	145	138
Hansen test, 2nd step	29.58	102.54	100.39	90.45	73.77	69.52	107.70	78.79	147.53	128.46
AB test AR (1)	-2.85***	-2.20**	-3.14***	-3.02***	-2.63***	-2.75***	-4.14***	-3.52***	-2.03**	-3.57***
AB test AR (2)	-0.21	-1.90*	0.28	-0.15	-1.85*	0.37	-0.77	0.18	-1.82*	-0.10

We use two-step system GMM estimations with Windmeijer's (2005) corrected standard errors. Wald 1 coefficients capture the joint test of the null hypothesis that both lags are equal to zero and are distributed as chi-square (χ^2) with two degrees of freedom. Wald 2 coefficients represent for each lagged variable the test of the null hypothesis that the sum of both lags is equal to zero. Statistical significance (10%, 5% and 1%) rejects the null hypothesis and confirms that x Granger-causes y. The Hansen test of over-identifying restrictions for GMM estimations tests whether the null hypothesis (applied instruments are not correlated with the error term) is valid. The Arellano-Bond (AB) test for serial correlation tests whether the null hypothesis (errors in the first-difference regression do not suffer from second-order serial correlation) is valid.

Turning to the robustness section (Table 2.7), results do not differ substantially. Our results confirm the "bad management" hypothesis for loan loss provision and liquidity as an indicator for bank risk. Similarly, we find evidence for the "bad luck" hypothesis, hence suggesting that economic downturns appear to have a negative impact on cost and profit efficiency (column 2 and 9). Most importantly, our results supports the notion that cooperative banks do not engage in moral hazard behaviour (column 1 and 7). Contrary, the management of cooperative banks appears to decrease risk exposure when bank capital declines. Nevertheless, we do no longer identify a significant positive effect of bank capital on profit efficiency. A reason might be that our broader measure of bank capital appears to blur the relationship.

In terms of market risk, results still suggest that banks with a higher level of market risk tend to hold more bank capital. Large banks have a higher capital ratio, however, the negative impact of total assets on liquidity is no longer significant. Finally, similar to table 2.6, we measure a positive effect of income diversification on bank capital, indicating that diversified banks hold more equity.

2.6 Conclusion

We applied Granger causality to evaluate intertemporal relationships among risk, efficiency, and bank capital using hand-collected data from German cooperative banks during the 2007 to 2014 period. Specifically, we investigated whether cooperative banks engage in moral hazard behaviour. We further moved beyond the existing literature as we employed another risk measure, liquidity risk, to evaluate all effects concerning bank liquidity within this context. At the same time, we used two different measures of bank efficiency, cost and profit efficiency, to analyse the intertemporal relationships among risk, efficiency and bank capital. These two efficiency measures are necessary since they reflect different managerial abilities.

Our results show strong evidence of a positive relationship between equity and credit risk, thus displaying that moral hazard (due to limited liability and deposit insurance) does not apply to cooperative banks. Our results reveal the opposite: Banks with low capital decrease their credit-risk exposure in following periods. This finding is – as expected – contrary to the existing literature (Berger and DeYoung, 1997; Williams, 2004; Fiordelisi et al., 2011), since we examined cooperative banks: the cooperative act: § 1 GenG is the basis for the business model of cooperative banks. The business model of cooperative banks is based on the interests of their customers, who are commonly locals. This characteristic of cooperative banks appears to attract a different set of bank managers. Those managers seem to contribute to the long-term prosperity of the bank. The fact that short-term shareholder interests (as a potential contributing factor for moral hazard behaviour) play no role for cooperative banks might support this notion.

Nevertheless, the supervisory board should carefully evaluate future management: we find that less capable bank managers appear to struggle in managing bank liquidity and credit risk. Thus, we can confirm the "bad management" hypothesis. Particularly liquidity has been widely neglected in previous literature, because the common perception has been that access to additional liquid funds is not an issue. However, the financial crisis as well as the recent euro sovereign debt crisis revealed that liquidity dried up for many banks due to increased mistrust in the banking sector. Thus, our study shows that banks may soon face liquidity issues after employing inefficient bank managers. Hence, we can conclude that cooperative banks do not suffer from moral hazard behaviour. However, they suffer from less capable managers. Like the study by Williams (2004), we do not measure any effect concerning the "skimping" hypothesis. Moreover, our results suggest that credit risk negatively Granger-causes cost and profit-efficiency, which confirms the "bad luck" hypothesis.

Finally, we showed that it is important to investigate intertemporal relationships among risk, efficiency and bank capital for cooperative banks since our results differ in parts substantially from the existing literature. This applies in particular to our finding of a positive relationship between capital and risk, which explicitly shows that cooperative banks do not engage in moral hazard behaviour. This outcome may exhibit eminent relevance for regulators, who should consider banks' business models before imposing adequate capital controls.

Appendix 2.A

Definition of variables

Variables	Symbol	Description
Loan loss provision	LLP	Loan loss provision over the total gross value of total bank loans
Liquidity Risk	LIQ	Calculated as (cash assets reserves + overnight debt due + trading assets + inventory on hands + money held in trust)/(total customer demand deposits)
Cost efficiency	$X - Eff$	Estimated using stochastic frontier analysis
Profit efficiency	$\pi - Eff$	Estimated using stochastic frontier analysis
Equity-to-assets ratio	E/TA	Total equity divided by total assets
Alternative equity-to-assets ratio	E_A/TA	Calculated as (total equity + preferred shares and hybrid capital + subordinated liabilities)/(total assets)
Overall market risk	$MRISK$	Calculated as (debt instruments issued by public-sector institutions and bills of exchange + bonds and other fixed-interest securities + shares and other non-fixed-interest securities)/(total assets – intangible assets – tangible assets – other assets)
Total assets	TA	Natural logarithm of total assets
Income diversification	ID	Calculated as (commission margin + trade margin + other earning assets)/(gross interest margin + commission margin + trade margin + other earning assets)
Change in GDP	GDP	Calculated as the percentage difference in German GDP between t-1 and t
Interest rate	$INTRATE$	Average ECB interest rate, calculated as daily weighted values for each year.
Unemployment rate	$UNEMP$	Unemployment rate (in %) in Germany (ILO)

Appendix 2.B

Correlation matrix of relevant regression variables

	$X-Eff$	$\pi-Eff$	LLP	LIQ	E/TA	E_A/TA	$MRISK$	TA	ID
$X-Eff$	1.0000								
$\pi-Eff$	-0.0433	1.0000							
LLP	0.1294	-0.1127	1.0000						
LIQ	0.0348	-0.1267	0.1855	1.0000					
E/TA	-0.0858	0.0934	-0.0736	-0.1921	1.0000				
E_A/TA	-0.0705	0.0955	-0.0642	-0.1506	0.9638	1.0000			
$MRISK$	0.0017	0.1286	-0.0277	-0.1566	0.0168	0.0138	1.0000		
TA	0.0353	-0.0478	-0.0594	-0.2184	-0.1642	-0.1755	0.0044	1.0000	
ID	-0.2674	0.0399	-0.1779	-0.1572	-0.0496	-0.0844	-0.0748	-0.0095	1.0000

Appendix 2.C

Results of cost-efficiency estimations using the stochastic frontier approach (maximum likelihood estimations)

Var	Par	Coef.	Std. Err.	P-Value	Var	Par	Coef.	Std. Err.	P-Value
Frontier									
$cons$	α_0	1.761	0.089	0.000	y_2w_2	λ_{22}	-0.012	0.008	0.127
y_1	β_1	0.223	0.131	0.088	y_2w_3	λ_{23}	-0.052	0.023	0.022
y_2	β_2	0.323	0.102	0.002	y_3w_1	λ_{31}	-0.009	0.017	0.610
y_3	β_3	0.468	0.099	0.000	y_3w_2	λ_{32}	-0.011	0.007	0.123
w_1	γ_1	0.730	0.102	0.000	y_3w_3	λ_{33}	0.025	0.016	0.119
w_2	γ_2	-0.109	0.058	0.063	y_1E	o_1	-0.933	0.322	0.004
w_3	γ_3	0.379	0.118	0.001	y_2E	o_2	0.222	0.291	0.446
E	η_1	-0.159	2.033	0.938	y_3E	o_3	0.495	0.217	0.023
T	θ_1	0.009	0.0288	0.757	y_1T	ρ_1	0.010	0.005	0.049
$y_{1,1}$	β_{11}	-0.035	0.010	0.001	y_2T	ρ_2	-0.013	0.004	0.002
$y_{1,2}$	β_{12}	0.0182	0.022	0.412	y_3T	ρ_3	0.003	0.003	0.330
$y_{1,3}$	β_{13}	0.028	0.019	0.144	w_1E	τ_1	0.495	0.450	0.271
$y_{2,2}$	β_{22}	0.209	0.016	0.000	w_2E	τ_2	0.180	0.155	0.247
$y_{2,3}$	β_{23}	-0.420	0.016	0.000	w_3E	τ_3	-0.536	0.283	0.059
$y_{3,3}$	β_{33}	0.204	0.008	0.000	w_1T	φ_1	0.003	0.005	0.517
$w_{1,1}$	γ_{11}	0.243	0.028	0.000	w_2T	φ_2	-0.005	0.002	0.029
$w_{1,2}$	γ_{12}	-0.030	0.023	0.196	w_3T	φ_3	0.000	0.008	0.963
$w_{1,3}$	γ_{13}	-0.376	0.047	0.000					
$w_{2,2}$	γ_{22}	0.026	0.008	0.001	μ_u				
$w_{2,3}$	γ_{23}	-0.041	0.023	0.074	$cons$		987.348	1766.586	0.576
$w_{3,3}$	γ_{33}	0.178	0.045	0.000	$INTRATE$		-15434.55	31706.21	0.626
E^2	η_{11}	-1.097	7.041	0.876	GDP		22935.66	30715.25	0.455
T^2	θ_{11}	0.001	0.002	0.527	$UNEMP$		-81620.77	109500.4	0.456
y_1w_1	λ_{11}	0.013	0.022	0.550					
y_1w_2	λ_{12}	0.017	0.009	0.061	σ_u		12.390	8.171	0.129
y_1w_3	λ_{13}	0.021	0.026	0.418	σ_v		0.032	0.001	0.000
y_2w_1	λ_{21}	0.006	0.017	0.703	$\lambda = (\sigma_u/\sigma_v)$		384.09	8.171	0.000

Appendix 2.D

Results of profit-efficiency estimation using the stochastic frontier approach (maximum likelihood estimations)

Var	Par	Coef.	Std. Err.	P-Value	Var	Par	Coef.	Std. Err.	P-Value
Frontier									
$cons$	α_0	5.302	0.346	0.000	y_2w_2	λ_{22}	0.058	0.030	0.053
y_1	β_1	0.526	0.475	0.268	y_2w_3	λ_{23}	-0.051	0.078	0.516
y_2	β_2	-0.983	0.376	0.009	y_3w_1	λ_{31}	0.039	0.065	0.541
y_3	β_3	0.117	0.362	0.746	y_3w_2	λ_{32}	0.004	0.026	0.880
w_1	γ_1	-0.404	0.348	0.246	y_3w_3	λ_{33}	-0.068	0.057	0.232
w_2	γ_2	-1.660	0.207	0.000	y_1E	o_1	4.918	1.163	0.000
w_3	γ_3	3.064	0.386	0.000	y_2E	o_2	1.400	1.032	0.175
E	η_1	5.624	7.484	0.452	y_3E	o_3	-3.192	0.748	0.000
T	θ_1	0.433	0.101	0.000	y_1T	ρ_1	0.008	0.180	0.639
$y_{1,1}$	β_{11}	0.162	0.039	0.000	y_2T	ρ_2	0.005	0.015	0.726
$y_{1,2}$	β_{12}	-0.213	0.084	0.011	y_3T	ρ_3	0.004	0.012	0.724
$y_{1,3}$	β_{13}	-0.113	0.073	0.121	w_1E	τ_1	-0.427	1.607	0.790
$y_{2,2}$	β_{22}	0.136	0.060	0.024	w_2E	τ_2	-0.401	0.588	0.495
$y_{2,3}$	β_{23}	0.102	0.059	0.086	w_3E	τ_3	3.812	0.985	0.000
$y_{3,3}$	β_{33}	0.005	0.033	0.881	w_1T	φ_1	0.052	0.019	0.007
$w_{1,1}$	γ_{11}	-0.444	0.099	0.000	w_2T	φ_2	-0.015	0.008	0.064
$w_{1,2}$	γ_{12}	-0.644	0.090	0.000	w_3T	φ_3	0.070	0.028	0.012
$w_{1,3}$	γ_{13}	0.696	0.165	0.000					
$w_{2,2}$	γ_{22}	-0.068	0.030	0.022	μ_u				
$w_{2,3}$	γ_{23}	-0.200	0.082	0.014	$cons$		88783.74	38916.07	0.023
$w_{3,3}$	γ_{33}	0.660	0.145	0.000	$INTRATE$		2509662	341905.1	0.000
E^2	η_{11}	-15.544	26.453	0.557	GDP		-159195	167116.8	0.341
T^2	θ_{11}	-0.004	0.006	0.505	$UNEMP$		-2563485	623451.3	0.000
y_1w_1	λ_{11}	-0.035	0.087	0.682					
y_1w_2	λ_{12}	-0.086	0.035	0.014	σ_u		35.995	8.462	0.000
y_1w_3	λ_{13}	0.248	0.090	0.006	σ_v		0.169	0.004	0.000
y_2w_1	λ_{21}	-0.109	0.067	0.106	$\lambda = (\sigma_u/\sigma_v)$		213.604	8.465	0.000

3 Earnings Management Modelling in the Banking Industry – Evaluating valuable approaches[12]

3.1 Introduction

Earnings management (EM) is a frequently discussed topic in both accounting and banking literature. This fact is not surprising, since EM is a very debatable, sometimes even obstructive issue when it comes to discussing earnings quality and the need of relevant and reliable information disclosure in its entirety (e.g. Ball and Shivakumar, 2005).

"Higher quality earnings provide more information about the features of a firm's financial performance that are relevant to a specific decision made by a specific decision-maker." (Dechow et al., 2010)

In this mind-set, research settings typically capture an opportunistic use of EM to manipulate the perception of the state of a company in favour of the management and/or company itself. Over the last three decades, various researches in the accounting and banking field have proposed models, which are able to estimate the non-discretionary variation of total or parts of total accruals. Based on these models, they isolate the discretionary part of the total accruals, which can be seen as a potential proxy for accounting-based EM. However, since a direct measurement is not possible,[13] these modelling attempts have considerably changed over time, with the goal to improve preciseness and credibility.[14]

For the accounting literature and its focus on non-financial industry companies, the development over time is easily despicable. Healy (1985) is the first author to propose a measurement of discretionary accruals. The author assumes that the non-discretionary part of total accruals equals the mean of total accruals during the observed period, indicating that a change in total accruals is attributable to

[12] This chapter is based on a working paper titled "Earnings Management Modelling in the Banking Industry – Evaluating valuable approaches" (Schaupp and Stralla, 2017), which is co-authored by Daniel Schaupp.

[13] Although a direct measurement is not possible, there are surveys investigating the existence and motivation behind EM, e.g. Graham et al. (2005). In spite of that, general possibility to pursue EM likely entails a certain utilization.

[14] See Dechow et al. (2010) for a general overview on the modelling of discretionary accruals in the other industries.

discretionary behaviour.[15] Jones (1991) resolves this restriction and proposes the first estimation-based model, which is able to determine non-discretionary parts from the coefficients of economic figures that reflect the state of the firm. The author uses change in revenue and property, plant and equipment as regressors. This modelling approach follows the idea that the applied economic variables are largely connected with non-discretionary, while the discretionary part can be captured as the residual from the regression. The modified Jones model (DeFond and Subramanyam, 1998) additionally considers possible discretionary revenue changes caused by manipulated changes in receivables, while Dechow and Sloan (1991) propose another model, which relaxes the assumption of constant non-discretionary accruals is their so-called „Industry Model". The authors also use an estimation model but assume that variations in the determinants of non-discretionary accruals are similar in firms of the same industry. Several other attempts to improve the modelling process exist.[16] McNichols (2002) develops one of the more recent models by combining the Jones model with a quality of accruals model proposed by Dechow and Dichev (2002). The McNichols model therefore adds regressors for lagged, current and forward operating cash flows to the specification.

Altogether, EM models in the accounting literature are characterized by two main properties. First, they approach the measurement from various directions, all of which are justifiable and reasoned. Second, a clear path of improvement is discernible, as the motivation for new models is connected with the flaws of the previous ones. Both characteristics are transferable to the EM modelling approach in the banking literature. Beatty and Liao (2014) compare various EM models and study these two properties in their comprehensive literature review. They discuss the first main difference of EM measurement in the banking industry, which is the focus on a single accrual, e.g., loan loss provisions (LLP). The authors provide three potential explanations for this focus. First, LLP is by far the most important accrual, amounting to 56% of total accruals and 34% of total accrual variance. Second, the

[15] The model by DeAngelo (1986) is a special case of Healy (1985), in which the author assumes that EM is not present in periods without EM incentives, hence defining the non-discretionary part of accruals as the total accruals in the year before the incentive year. Both models suffer under the assumption of permanence of non-discretionary accruals while ignoring the economic context.

[16] See Dechow et al. (2003) and Dechow et al. (1995) for two major attempts to study and develop the discretionary accruals modelling process for the non-financial industries.

focus on LLP could be related to the urge of minimizing measurement error. When total accruals are considered, mapping non-discretionary variation might be more prone to measurement issues. Third, data availability may also play a role, as major databanks gradually developed and provided all variables for more complex approaches. The reasons are plausible, which is why we focus on LLP Models in our extensive analysis based on previous studies published in highly ranked accounting and banking journals. The second main difference between EM in accounting and banking is the missing comprehensive discussion and examination of the applied models. Beatty and Liao (2014) state that there is no "consensus in banking studies on how to best model discretionary accruals." What is important, existing models vary considerably in complexity and choice of pattern groups. In addition, and in contrast to accounting literature for the non-financial industries (e.g. Dechow et al., 1995; Young, 1999; Peasnell et al., 2000), there is no study addressing this gap, which is why we try to fill this academic void with our study.

Our results indicate that non-performing loan patterns are the most important pattern group when it comes to separating LLP into discretionary and non-discretionary parts, while loan loss reserve and/or net charge-off patterns can enhance the modelling, though are less important. Consequently, EM proxies derived from models that are more complex predict potential EM more accurately, while in settings of data limitations, appropriate models still exist. Furthermore, we find that the relationship between LLP and a common set of control variables might be non-linear in contrast to common assumptions of linearity, while we identify growth, loan intensity, income diversification and operating cash-flow patterns as possible omitted correlated variables that could improve the quality of discretionary LLP. At last, we find that dynamic modelling seems to improve explanatory power, while they might explain some discretionary part of total LLP, which can lead to biased inferences. What is more, endogeneity robust estimation cannot solve this problem.

Altogether, we contribute to the current literature in two major ways. First, we provide an overview of the differences between various EM estimation procedures and analyse the respective regression pattern groups. Furthermore, we extent our research on models for situations of data availability issues, which are especially relevant for researchers that investigate non-commercial banks. Second, we apply several test procedures from banking and accounting literature to investigate measurement errors, omitted variable biases and predictive power of the applied EM models. Based on our results, future research should be able to identify an appropriate specification and further improve the modelling of EM to enhance the validity of inferences drawn from regressions.

The remainder of the paper is organized as follows. Section 3.2 presents a brief overview of EM modelling in the banking literature and provides an extensive analysis of the specifications used in prior literature, whereupon we set up various models for our test procedures. Section 3.3 contains the research design, including data and sample selection, discussion of statistical issues and the empirical test procedures to test the validity of the models. Section 3.4 presents the results from first-stage regressions and the uni- and multivariate findings of the empirical test procedures. Section 3.5 presents a summary and conclusions.

3.2 Earnings management in banks and modelling discretionary LLP

3.2.1 Earnings Management in Banks

Major parts of the earnings and financial reporting quality literature focus on evaluating the degree of EM in non-financial firm samples.[17] Consecutively, EM in banks has evolved as a distinct field of research, in particular because possibilities and incentives to pursue EM differ significantly and therefore determine customized methods of measurement.

Beatty and Liao (2014) provide an extensive theoretical and empirical overview of banking research in accounting. Among various related questions, they elaborate and discuss why banks use discretion in their financial reporting to foster certain opportunistic goals, namely capital management (e.g. Wahlen, 1994; Beatty et al., 1995; Collins et al., 1995; Kim and Kross, 1998) and smoothing of earnings (e.g. Ahmed et al., 1999; Anandarajan et al., 2007; Beatty and Liao, 2009; Bouvatier et al., 2014). Bushman (2014) complements Beatty and Liao (2014) and highlights the risk-taking aspect of opportunistic reporting behaviour. Acharya and Ryan (2016)

[17] Dechow et al. (2010) give an extensive literature overview for the quality of earnings research. When discussing earnings management, they also focus on the measures that are used in studies that cover non-financial industry questions.

extensively discuss selected papers and provide suggestions for regulation to enhance the stability of the financial system.

All these studies highlight the decisiveness of discretionary accounting choices in banks and highlight the importance of research in this field. Essentially, for adequate inferences to be drawn, underlying methodological approaches have to be adequate. Beatty and Liao (2014) highlight this by giving an idea of the multitude of measures and actively stating the importance of a thorough analysis of the applied models and the modelling approach. Although applying significantly different models, most studies use some sort of discretionary accruals, which is equivalent to the non-financial part of the accounting literature. Models vary over time in the analysed dependent variables. For example, some studies use discretionary loan loss reserves (e.g. Hasan and Wall, 2004; Jin et al., 2016) or realized gains and losses (Beatty et al., 1995; Collins et al., 1995; Beatty and Harris, 1998; Beatty et al., 2002). Yet, most papers regard LLP as the most important vehicle for EM in banks (e.g. Bushman, 2014; Lobo, 2017), because LLP account for 56% of the total accruals (e.g. Beatty and Liao, 2014) as well as 15-20% of the earnings before taxes and loan loss provisioning ($EBTP$) (e.g. Lobo, 2017). In particular, a bank using higher LLP can intentionally build up loan loss reserves in years of high performance for means of improving earnings numbers when EBTP is low (e.g. Sutton, 1997; Levitt, 1998). Models with a total accrual approach, equivalent to the industry models, would be likely to produce additional measurement error rather than feasible discretionary accruals. Several studies (e.g. Dechow et al., 1995; Peasnell et al., 2000; McNichols, 2002; Dechow et al., 2010) already show that total accrual designs are associated with high degrees of measurement error in non-financial settings, particularly due to omitted correlated variables and the complexity of identifying appropriate normal accrual regressors. What is even more important, for financial entities, the remaining 44% of the total accruals are unlikely to be subject to discretion since standard setting for banks has consequently limited accounting flexibilities (e.g. Beatty and Liao, 2014).

Accounting standards for credit losses have likewise significantly changed over time and shaped the degree of discretion in provisioning of loan losses for banks. While the respective rules in the 1990s relied heavily on future-oriented fundamentals, e.g. non-performing loans, to evaluate their loan loss reserves (e.g. Ludwig, 2009; Beck and Narayanamoorthy, 2013; Beatty and Liao, 2014), the SEC and FASB issued the Staff Accounting Bulletin (SAB) 102 and the Federal Financial Institutions Examination Council (FFIEC) Policy Statement (e.g. FFIEC, 2001; SEC, 2001) for fiscal years after 2001. These emphasized a market-to-market based evaluation in form of the incurred loss model, e.g. focus on already occurred loss events, for means of loan loss provisioning, leaving less room for discretion. Subsequently there has been a constant field of tension between the decision usefulness of accounting standards and the regulatory prevention of bank failures, particularly about the pro-cyclicality of provisioning for loans and leases under the incurred loss model (e.g. Financial Stability Forum, 2009; Bushman and Williams, 2012). This has again lead to changes in LLP accounting standards, e.g. the introduction of the expected loss model in IFRS 9 and the current expected credit loss model in ASC 326. They leave banks again with more discretion in terms of inclusion of future estimates (e.g., Bushman and Williams, 2015; Lobo, 2017; PwC, 2017) for fiscal years 2018 (IFRS 9) and 2020 (ASC 326).[18] Altogether, LLP are likely to remain the most important discretionary accrual for banks, which is why we concentrate on the discretionary LLP models throughout our analysis.

3.2.2 Specification analysis

We focus on a sample of studies from the accounting and finance literature in the time-period 1990-2017. We incorporate all regression-based analyses published in journals with an h5-index above 50 or an SRJ above 0.500.[19] We identify 39 papers using discretionary LLP as their EM or EQ measure and capture time-period analysed, setting, one vs. two-step models and specifications.[20] We identify 8 pattern groups in the literature.[21] A brief look at panel A of table 3.1 shows the

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[18] While, neither framework requires a specific methodology, IFRS 9 and ASC 326 require "the estimate of expected credit losses […] [to] consider historical information (past events), information about current conditions, and reasonable and supportable forecasts of future events and economic conditions, as well as estimates of prepayments." (PwC 2017, p. 6) In addition, US-GAAP does not require multiple forward-looking scenarios as long as the scenario is carefully selected and represents the expected credit loss. Altogether, US-GAAP and IFRS guidelines seem to provide room for estimates about the future and therefore discretion.

[19] The analysed papers use one- and two-step approaches, where one-step means inclusion of variables of interest in the first-step regressions together with the non-discretionary LLP regressors, while two-step means separate, second-step variable of interest analyses with discretionary LLP as a dependent variable. We focus on a two-step approach and further comment on this design choice whenever applicable.

[20] See Appendix 3.B for the list of specifications.

[21] We do not report frequencies for lagged LLP as a possible pattern group, since we regard the decision to include these variables as a methodological one (static vs. dynamic modelling) and not a choice of patterns. Bouvatier et al. (2014) use LLP_{it-1} and Fonseca and Gonzalez (2008) use

magnitudes of usage for all pattern groups as well as the specific patterns of each group. Most papers (76.9 percent) use total loans and non-performing loans to estimate non-discretionary LLP, whereas 48.7 percent respectively 43.6 percent of the studies use loan loss reserves respectively net loan charge-offs. In addition, a further set of controls is included by 59.0 percent of the studies for capital requirement ratios and earnings before provisioning, while 35.9 percent use a variable for the overall size of the bank.[22] We separately study the total loans and non-performing loans pattern groups in panel B & C of table 3.1, since most studies use more than one regressor to capture these pattern groups. Again, we find a variety of patterns of both groups, highlighting the importance of a structured and thorough analysis. For non-performing loans, most studies use a combination of NPL_{it-1} and ΔNPL_{it} (33.3 percent), while for the total loans group, ΔTL_{it} is the predominantly used (36.7 percent) pattern.

In the following, we comment on every pattern group and present respective reasoning for the choice of regressors. We further discuss the model specification parts and gradually develop a specification for our further analysis.

LLP_{it-2} in addition to implement a dynamic approach. We further discuss static vs. dynamic modelling in section 2.4.

[22] We find 23 papers with a one-step approach, while 16 papers comprehend discretionary LLP as the residual from a first stage model and test their variables of interest in a separate second stage. In addition, there is no development over time in preference of one- or two-step approaches. We note that not all papers seek to draw inferences about EM behaviour, e.g. Liu and Ryan (1995) study the influence of bank loan-portfolio composition on loan loss provisioning. Rather, all papers seek to explain the variation of non-discretionary LLP.

Table 3.1
Specification pattern distribution

Panel A: All regressors

Pattern group	**Pattern**	**Number of pattern papers**	**(percentage of pattern group papers)**	**Number of pattern group papers**	**(percentage of papers)**
Total loans	ΔTL_{it}	21	(70.0%)	30	(76.9%)
	TL_{it}	12	(40.0%)		
	$TL\_CATEGORIES_{it}$	9	(30.0%)		
	ΔTL_{it+1}	1	(3.3%)		
	TL_{it-1}	1	(3.3%)		
Non-performing assets/loans	ΔNPA_{it}	22	(73.3%)	30	(76.9%)
	NPA_{it-1}	13	(43.3%)		
	NPA_{it}	9	(30.0%)		
	ΔNPA_{it+1}	6	(20.0%)		
	ΔNPA_{it-1}	3	(10.0%)		
	ΔNPA_{it-2}	2	(6.7%)		
	NPA_{it-2}	2	(6.7%)		
	ΔNPA_{it-3}	1	(3.3%)		
Capital requirement ratio	$CAPB_{it}$	16	(94.1%)	23	(59.0%)
	$CAPB_{it-1}$	7	(5.9%)		
Earnings before provisioning	$EBTP_{it}$	23	(100.0%)	23	(59.0%)
	$\Delta EBTP_{it}$	1	(4.3%)		
	$\Delta EBTP_{it+1}$	1	(4.3%)		
Loan loss allowances/reserves	ALW_{it-1}	13	(68.4%)	19	(48.7%)
	ALW_{it}	6	(31.6%)		
Net loan charge-offs	NCO_{it}	16	(94.1%)	17	(43.6%)
	ΔNCO_{it}	1	(5.9%)		
Bank size	$SIZE_{it}$	12	(85.7%)	14	(35.9%)
	$SIZE_{it-1}$	2	(14.3%)		
	$\Delta SIZE_{it}$	1	(7.1%)		
Macroeconomic variables (ΔGDP_{jt}, $\Delta UNEMP_{jt}$, $\Delta LandPrice_{jt}$, $CSRET_{jt}$, ΔBFI_{jt}, ΔSDA_{jt})				13	(33.3%)

Panel B: Non-performing assets/loans regressors

Pattern	**Number of NPA papers**	**(percentage of NPA papers)**
NPA_{it-1} ΔNPA_{it}	10	(33.3%)
NPA_{it}	5	(16.7%)
ΔNPA_{it}	4	(13.3%)
NPA_{it} ΔNPA_{it}	3	(10.0%)
NPA_{it-2} NPA_{it-1} ΔNPA_{it} ΔNPA_{it+1}	2	(6.7%)
NPA_{it} ΔNPA_{it}	1	(3.3%)
ΔNPA_{it-2} ΔNPA_{it-1} ΔNPA_{it} ΔNPA_{it+1}	1	(3.3%)
ΔNPA_{it} ΔNPA_{it+1}	1	(3.3%)
NPA_{it-1} ΔNPA_{it-1}	1	(3.3%)
ΔNPA_{it-3} ΔNPA_{it-2} ΔNPA_{it-1} ΔNPA_{it}	1	(3.3%)
ΔNPA_{it+1}	1	(3.3%)

Panel C: Total loans regressors		
Pattern	Number of TL papers	(percentage of TL papers)
ΔTL_{it}	11	(36.7%)
TL_{it}	4	(13.3%)
TL_{it} ΔTL_{it} $TL\_CATEGORIES_{it}$	4	(13.3%)
TL_{it} ΔTL_{it}	4	(13.3%)
$TL\_CATEGORIES_{it}$	4	(13.3%)
ΔTL_{it} $TL\_CATEGORIES_{it}$	1	(3.3%)
TL_{it-1} ΔTL_{it}	1	(3.3%)
ΔTL_{it+1}	1	(3.3%)

Pattern distributions are based on the loan loss provision specifications of the papers stated in Appendix 3.B. All variables are defined in Appendix 3.A.

3.2.2.1 Total loans

Kanagaretnam et al. (2010a) elaborate that a higher level of loans results in a higher level of provisions (e.g. also Kim and Kross, 1998). Therefore, they expect a positive relation. However, Bikker and Metzemakers (2005) argue that this relationship would only be true in a world of prudent and forward-looking banks, which is not in line with a reality where banks exaggerate expectations to minimize provisioning. To our understanding, the expected sign is unpredictable due to uncertainty about the incremental quality of the loan portfolio. What is more, changes in total loans can be seen as changing assessment of future default risk (e.g. Lobo and Yang, 2001; Bikker and Metzemakers, 2005), hence an increase would go hand in hand with an increase in provisioning (expected sign positive).[23] While 36.7 percent of all papers with a total loans pattern choose to include only ΔTL_{it}, only 13.3 percent apply TL_{it} and ΔTL_{it} (see panel C of table 3.1). However, we choose to follow the latter approach, since we expect changes in assessment of future credit risk and level of actual credit risk to have distinct influences on non-discretionary LLP.[24]

3.2.2.2 Non-performing assets/loans[25]

Loans, whose payments are due for more than 90 days, are categorized as non-performing. Most studies include non-performing assets, as a higher level of

[23] Some studies note that the effect of changes in loans could also be ambiguous if changes in total loans are not caused by changes in credit default risk. Then, the effect of changes in loans might be ambiguous, just like the effect of total loans, because of uncertainty about the quality of the loan portfolio (e.g. Kanagaretnam et al., 2004; Hamadi et al., 2016).

[24] Kim and Kross (1998) also formulate $LLP_{it} = f(TL_{it}, TL_{it-1}, NPA_{it}, NPA_{it-1}, NCO_{it})$, while including change and level of total loans implicitly maps lagged total loans.

[25] Throughout our study, the two terms non-performing loans and non-performing assets are used interchangeably.

non-performing assets indicates problems with the loan portfolio (e.g. Wahlen, 1994; Kanagaretnam et al., 2010a; Hamadi et al., 2016). These problems force banks to act, leading to higher provisioning. This argumentation holds true for the change in non-performing assets, as an increase reflects an actual change in default rate, e.g., improving or deteriorating loan portfolio quality (e.g. Beatty et al., 1995; Kim and Kross 1998; DeBoskey and Jiang, 2012). Prior studies use patterns for level and change in non-performing assets with different lags. Based on our further analysis of the pattern group in panel B of table 3.1, we add the pattern with the highest frequency of use , NPA_{it-1} and ΔNPA_{it} (33.3 percent of all NPA papers and 25.6 of all papers), to our specification pattern list.[26] The expected signs for the two coefficients are positive.

3.2.2.3 Set of further controls (capital requirement ratio, earnings before provisioning and bank size)

Papers using one- and two-step approaches apply a multitude of confounding control variables to cancel out omitted variable biases. One component is the inclusion of important capital ratios to control for banks' incentives to manage their capital adequacy (e.g. Beatty et al., 1995; Ahmed et al., 1999; Bouvatier et al., 2014). Furthermore, prior research controls or tests for the earnings smoothing incentives of banks. For the industry models, Kothari et al. (2005) highlight that without appropriate control for performance, the resulting EM proxies are biased, e.g. performance of the firm significantly influences the magnitude of the non-discretionary accruals and therefore exclusion leads to a bias of the discretionary accruals. Since banking models focus on LLP as only one accrual and most studies follow this approach, they apply performance before provisioning (e.g. Ahmed et al., 1999; Anandarajan et al., 2007; Leventis et al., 2011; Bushman and Williams, 2015).[27] Panel A in table 3.1 highlights that 59 percent of the analysed papers control for capital requirement ratios and

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[26] Since $NPA_{it-1} + \Delta NPA_{it} = NPA_{it}$, this pattern simultaneously captures the influence of current non-performing loans, which is the pattern with second highest frequency of use.

[27] Kothari et al. (2005) distinguish between inclusion of a performance control and actual matching. We assume actual matching to over-correct for performance, especially for discretionary LLP, since they are recurrent and systematic. E.g., a bank has positive discretionary LLP due to high EM and the matched bank has comparably high positive discretionary LLP, not due to bad fitting of the model, but because both banks pursue EM, e.g. have comparable earnings smoothing or capital management incentives. Performance matching would correct for actual EM and hence distort the results on the null hypothesis of no EM in a way that it accepts the null. We therefore only use EBTP as an additional regressor.

earnings before provisioning, while the overwhelming majority use current year proxies.[28] We follow this approach and add $EBTP_{it}$ and $CAPB_{it}$ to our specification pattern list. As a third major control, 35.9 percent of the papers control for bank specific size (e.g. Agarwal et al., 2007; Beatty and Liao, 2011; Beck and Narajanamoorthy, 2013). Again, we decide upon the pattern option with the highest frequency of use (85.7 percent of the papers with a size pattern), e.g., $SIZE_{it}$.

3.2.2.4 Loan loss allowances/reserves:

Allowances for loan losses capture past decisions about loan loss provisioning. The effect on current LLP and therefore its sign depends on the relation between past provisioning, the actual demand for provisioning and loan loss recognition (e.g. Beatty et al., 1995; Kanagaretnam et al., 2010a/b; DeBoskey and Jiang, 2012). If larger past provisioning, summarized by loan loss reserves, is associated with increases in loss recognition, especially in times of distrust and high uncertainty, larger reserves should be associated with larger current loan loss provisions, hence we expect a positive sign (e.g. Wahlen, 1994; Ahmed et al., 1999; DeBoskey and Jiang, 2012). However, for constant loss recognition, we expect contrasting over-/underprovisioning effects on current-year non-discretionary LLP, indicated by a negative sign. We find that 68.4 percent of the studies with a loan loss allowance pattern use lagged allowances as a regressor, which is we add ALW_{it-1} to our specification list.[29]

3.2.2.5 Net loan charge-offs:

Beaver and Engel (1996) see current loan net charge-offs as a source of information about future charge-offs. In comparison to non-performing loans, net charge-offs are a less noisy indicator of future losses (e.g. Beck and Narayanamoorty, 2013). When net charge-offs are high, current loan quality is rather low and therefore higher provisioning is expected.

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[28] We note that capital adequacy ratios are applied in a wide variety, e.g., tier 1 capital to risk-weighted assets, tier 1 capital to total assets, tier 1 and tier 2 capital ratios, etc. We test for the validity of our results when changing the capital adequacy proxy used. However, our results are not dependent on this design choice.

[29] We note that small differences in the specifications, e.g., including ALW_{it-1} (13 times used) or ALW_{it} (6 times used), might also be due to sample specific considerations of autocorrelation.

3.2.2.6 *Macroeconomic variables:*

Ahmed et al. (1999) point out that macroeconomic controls might have an effect on non-discretionary LLP. The performance and loan repayment behaviour of companies and private households are highly influenced by the overall economic state of the respective country. In particular, increases in unemployment or decreases in GDP may point to a deterioration of the economic situation. In such cases, a decrease in loan quality is highly likely, imposing higher demand for LLP (e.g. Bikker and Metzemakers, 2005; Bushman and Williams, 2012; Beck and Narayanamoorty, 2013). However, Kanagaretnam et al. (2004) propose that inclusion of changes in non-performing loans and net charge-offs will control for macroeconomic effects. What is more, some papers (e.g. Laeven and Majnoni, 2003; Kanagaretnam et al., 2014) use year and/or country fixed effects, which work similar. We regard continuous macroeconomic controls to be more precise and add ΔGDP_{jt} and $\Delta UNEMP_{jt}$ to our pattern list.

3.2.3 Static LLP Models

Based on our specification analysis and discussion, we use different sets of the specification parts to construct the following first-stage regressions:

$$\begin{aligned} LLP_{it}/TA_{it-1} = {} & \alpha_0 + \beta_1\, NPA_{it-1}/TA_{it-1} + \beta_2\, \Delta NPA_{it}/TA_{it-1} \\ & + \beta_3\, ALW_{it-1}/TA_{it-1} + \beta_4\, TL_{it}/TA_{it-1} \\ & + \beta_5\, \Delta TL_{it}/TA_{it-1} + \beta_6\, NCO_{it}/TA_{it-1} \\ & + \beta_7\, \Delta GDP_{jt}/GDP_{jt-1} \\ & + \beta_8\, \Delta UNEMP_{jt}/UNEMP_{jt-1}\ \{+\beta_9 SIZE_{it} \\ & + \beta_{10}\, EBTP_{it}/TA_{it-1} \\ & + \beta_{11} CAPB_{it}\}\ [+\beta_{12}\, NPA_{it-2}/TA_{it-1} \\ & + \beta_{13}\, \Delta NPA_{it+1}/TA_{it-1}] + \varepsilon_{it} \end{aligned} \tag{1}$$

where, LLP is loan loss provision, NPA is non-performing assets, ALW is loan loss allowances, NCO is net loan charge-offs, TL is total loans and TA is total assets for firm i in year t. GDP / $UNEMP$ is gross domestic product / unemployment rate for country j (the respective firm i is located in) in year t. $SIZE$ is defined as the natural logarithm of total assets, $EBTP$ is earnings before taxes and provisioning scaled by total assets and $CAPB$ is a capital adequacy ratio, calculated as tier 1 capital to lagged total assets.

Model ***S1*** uses all regressors that are not recorded in brackets ($\beta_1 - \beta_8$). We include the set of further controls for size, pre-provisioning performance and capital ratio in ***S2*** by adding the regressors in curly brackets ($\beta_9 - \beta_{11}$) to the specification. In comparison, ***S3*** includes the additional set of non-performing loans in square brackets, while excluding the set of further controls in curly brackets (include $\beta_{12} - \beta_{13}$, exclude $\beta_9 - \beta_{11}$). At last, model ***S4*** uses all regressors in Eq. (1).

3.2.4 Dynamic LLP Models

Models ***S1-S4*** are static regressions. In contrast, some authors (e.g. Laeven and Majnoni, 2003; Fonseca and Gonzalez, 2008; Bouvatier et al., 2014)[30] introduce dynamic EM models by including the lagged dependant variable (lagged LLP) as an independent variable. This change in the modelling of discretionary LLP assumes that autoregressive effects of the first order have a significant influence on the variation of total LLP, which cannot be captured by the non-discretionary regressors already presented in the static LLP models. E.g., Laeven and Majnoni (2003) mention the adjustments in loan loss provisioning when banks approach equilibrium reserve levels.

To investigate the differences in fit between static and dynamic approaches, we define model ***D1-D4*** as dynamic versions of models ***S1-S4***. Therefore, we add β_{14} to each of the specifications of ***S1-S4***:

$$\begin{aligned} LLP_{it}/TA_{it-1} = {} & \alpha_0 + \beta_1\, NPA_{it-1}/TA_{it-1} + \beta_2\, \Delta NPA_{it}/TA_{it-1} \\ & + \beta_3\, ALW_{it-1}/TA_{it-1} + \beta_4\, TL_{it}/TA_{it-1} \\ & + \beta_5\, \Delta TL_{it}/TA_{it-1} + \beta_6\, NCO_{it}/TA_{it-1} \\ & + \beta_7\, \Delta GDP_{jt}/GDP_{jt-1} \\ & + \beta_8\, \Delta UNEMP_{jt}/UNEMP_{jt-1}\ \{+\beta_9 SIZE_{it} \\ & + \beta_{10}\, EBTP_{it}/TA_{it-1} \\ & + \beta_{11} CAPB_{it}\}\ [+\beta_{12}\, NPA_{it-2}/TA_{it-1} \\ & + \beta_{13}\, \Delta NPA_{it+1}/TA_{it-1}]\ + \beta_{14}\, LLP_{it-1}/TA_{it-1} + \varepsilon_{it} \end{aligned} \tag{2}$$

3.2.5 Basic Models

Models ***S1-S4*** and ***D1-D4*** represent the state of the art with regard to the estimation of discretionary LLP. Therefore, these specifications should be able to disentangle

[30] Laeven and Majnoni (2003) include a dynamic version (using lag-1 and lag-2 LLP) of their model as an alternative specification.

discretionary LLP from their non-discretionary part to a degree where the resulting proxies are viable for EM propositions. Hence using these models should enable researchers to draw conclusive inferences with significantly low probabilities of type I errors when empirical designs apply sufficient controls.

However, some studies within special settings deliberately leave out non-performing loans (e.g. Cavallo and Majnoni, 2002; Bikker and Metzemakers, 2005; Bouvatier et al., 2014, who report data availability as a reason)[31], net loan charge-offs (e.g. Beatty and Liao, 2011; DeBoskey and Jiang, 2012; Cohen et al., 2014) and loan loss allowances (e.g. Cheng et al., 2011; Bushman and Williams, 2012; Bouvatier et al., 2014) as regressors, while numerous studies do so uncommented.[32] To investigate the validity of simplified approaches, we set up basic models. Based on our specification analysis as well as our own data availability, we identify three variables, which are predominantly accountable for the reduction of data sets, namely non-performing loans/assets, allowance for loan losses and net charge-offs. The models are characterised as follows:

$$\begin{aligned} LLP_{it}/TA_{it-1} = \alpha_0 &\{+\beta_1\, NPA_{it-1}/TA_{it-1} \\ &+ \beta_2\, \Delta NPA_{it}/TA_{it-1}\}[+\beta_3\, ALW_{it-1}/TA_{it-1}] \\ &+ \beta_4\, TL_{it}/TA_{it-1} \\ &+ \beta_5\, \Delta TL_{it}/TA_{it-1}\ (+\beta_6\, NCO_{it}/TA_{it-1}) \\ &+ \beta_7\, \Delta GDP_{jt}/GDP_{jt-1} + \beta_8\, \Delta UNEMP_{jt}/UNEMP_{jt-1} \\ &+ \varepsilon_{it} \end{aligned} \tag{3}$$

For model ***B1***, we exclude all brackets (β_{1-3} and β_6) and obtain a model, which is only dependent on the development of two factors: the amount of loans and macroeconomic effects. For model ***B2-B4***, we include either NPA, ALW or NCO, for models ***B5-B7*** we include combinations of two of the three terms. We estimate the basic models to gain insights regarding two questions. First, which variables are important when it comes to splitting discretionary and non-discretionary LLP? Hence, we investigate differences in R^2 between the basic models. Second, does an exclusion of seemingly important variables cause biases and/or lead to substantially

[31] Data availability is particularly important for researchers, who focus on bank types other than commercial banks and/or smaller (non-US) samples, due to less pronounced regulations and/or disclosure requirements.

[32] Some studies use the excluded specification parts in untabulated robustness tests (e.g. Bushman and Williams, 2012).

varying results on the second stage, especially when it comes to the predictive power of the resulting proxies for EM?

3.3 Research design

3.3.1 Data and sample selection

We obtain an initial data set containing 14,547 firm-year observations from all 1,445 financial institutions available in Thomson Reuters Datastream database with industry codes between 6011-6099 and 6710-6719 for the time-period 2005-2015. We exclude all observations with annual reports following any other standards than US-GAAP and IFRS, which accounts for a loss of 4,888 observations. We furthermore have to exclude all observations with insufficient data for estimation of our models. This step accounts for a loss of 7,076[33], leaving 2,583 firm-year observations as the remaining sample. Since more than 70 percent of the observations are US-banks and regulatory differences between countries, even though having decreased in the post-BASEL I + II era (e.g. Beatty and Liao 2014), may influence the measurement of EM, we decide to use a final sample of 1,854 observations containing only banks from the United States.[34] We winsorize all incorporated variables at the 1st and 99th percentile to control for outliers that could majorly influence our results. Table 3.2 gives an overview of the sample selection procedure and the distribution of observations over the sample period.[35]

[33] Especially the data availability concerning non-performing loans variables, net loan charge-offs and loan loss reserves leads to this significant sample decrease by about three quarters.

[34] The remaining quarter of the remaining sample comprises 50 countries with very few observations each. In addition, the setting of most parts of the related literature focuses only on US banks, too.

[35] We apply lagged and forward variables, which results in a final sample period from 2007-2014.

Table 3.2
Sample selection procedure and distribution by years

Selection mode	Number of observations
All companies from 2005-2015	14,547
Less:	
Not US-GAAP or IFRS as reporting standards	4,888
Missing data for estimation of models	7,076
Non-US firm-year observations	729
Final Sample	1,854
Distribution by years	
2007	173 (9.3%)
2008	175 (9.4%)
2009	180 (9.7%)
2010	187 (10.1%)
2011	158 (8.5%)
2012	364 (19.6%)
2013	334 (18.0%)
2014	283 (15.3%)

3.3.2 Empirical test procedures

3.3.3 Statistical issues

The statistical issues in empirical accrual modelling have already been highlighted in earlier studies (e.g. McNichols and Wilson, 1988; Dechow et al., 1995; McNichols, 2000). We follow their discussion and partition total loan loss provisions (LLP) into a non-discretionary ($NLLP$) and discretionary ($DLLP$) component:

$$LLP_{it} = DLLP\_true_{it} + NLLP\_true_{it} \tag{4}$$

Since we cannot observe $DLLP\_true_{it}$, research uses a simple linear panel regression framework with N individuals and K regressors to comprehend a proxy $DLLP_{it}$:

$$LLP_{it} = \alpha_0 + \boldsymbol{\beta}\, \boldsymbol{NAX}_{it} + u_{it} \tag{5}$$

LLP_{it} is the total LLP of bank i in year t, $\boldsymbol{NAX}_{it}$ is a $N \times K$ matrix of certain variables that are assumed to cause variation, which is connected to non-discretionary business decisions and developments. $DLLP_{it}$ is calculated as the residual u_{it} of regression (5), with a certain measurement error η_{it}:

$$DLLP_{it} = DLLP\_true_{it} + \eta_{it} \tag{6}$$

The properties of η_{it} determine whether $DLLP_{it}$ is a good or a noisy measure. These properties are dependent on the accuracy of our non-discretionary regressors in estimating the non-discretionary variation, e.g., $NLLP\_true_{it}$:

$$\eta_{it} = NLLP_{it} - NLLP\_true_{it} \tag{7}$$

Consequently, research studies use the following simple linear regression:

$$DLLP_{it} = \alpha_0 + \beta_1 VOI_{it} + \boldsymbol{\beta}\, \boldsymbol{X}_{it} + \varepsilon_{it} \tag{8}$$

VOI_{it} is a dichotomous or continuous variable of interest that is hypothesized to exert significant influence on discretionary LLP, e.g., EM. $\boldsymbol{X}_{it}$ is another $N \times K$ matrix that captures a set of control variables that influences the variation in the discretionary dependent variable, while ε_{it} is an error term that captures the individual heterogeneity of the bank i in year t.

If the coefficient for the variable of interest (β_1) has the hypothesised sign and is statistically significant at the conventional (0.01, 0.05, 0.1) levels, researchers consider their results to support their hypotheses. In this situation, the significance of coefficient β_1 can be biased when the variable of interest is correlated with the error η_{it}. In particular, this will be the case when $NLLP\_true_{it}$ is correlated with VOI_{it} but $NLLP_{it}$ does not capture $NLLP\_true_{it}$ properly, e.g., η_{it} is not just white noise.

3.3.4 Empirical design

We test the validity of the discretionary LLP proxies in several analyses. First, we compare the coefficients and the goodness-of-fit of the first-stage regressions. Second, we check for measurement errors of the discretionary LLP measures by applying a method proposed by Dechow et al. (1995) and applied by Peasnell et al. (2000). The test evaluates the rate of rejection of the null hypothesis of no EM when actually no EM exists (type 1 error). Consequently, we study the rate of incorrect rejection of the null hypothesis. We therefore use a randomly selected sample of 25 percent of the firm-year observations from the total sample[36] and compute a PART

[36] We follow Peasnell et al. (2000) and note that this percentage should capture a typical, dichotomous variable of interest with no systematic influence on our EM proxy. We point to the selection process and the probabilities to draw observations that bear a certain communal characteristic that could lead to a significance, which decreases with increasing number of observations drawn from the sample for our PART variable. We coincide with Peasnell et al. (2000) and Dechow et al. (1995) that this is simply a test of whether the Gaussian assumptions underlying our regressions in Eq. (1)-(3) are satisfied.

variable that takes up the value of one if the firm-year observation is located in the randomly selected sample, and zero otherwise. We study significances of the randomised PART variable, which should not have any significant influence on the dependent variable. We repeat the test procedure 10,000 times for each of the models to cancel out the problem of randomly selecting firm-year observations that actually have significant influences on the dependent variable.

Third, we address omitted variable problems of the first stage using two different approaches. First, we study the performance error bias of our coefficients and residuals (e.g. Kothari et al., 2005). Therefore, we use a sampling method (e.g. Dechow et al., 1995) to select extreme performance firm-year observations and compute another PART dummy variable. We then estimate second-stage univariate regressions once again. When financial performance is one major omitted variable that can majorly improve specification of the model, the coefficients on the PART variable should indicate a significant influence on conventional levels. Peasnell et al. (2000) note that having a systematically selected sample, endogeneity might actually lead to correct significances and therefore false rejections of models. In particular, observations in the extreme performance parts of the distributions might represent very successful or unsuccessful banks and lead to systematic EM approaches, i.e., very successful banks in the positive extreme part of the distribution might use considerable negative LLP to build up loan loss allowances and vice versa.[37] We address this problem in more detail in section 4.4.

We additionally use a more general OMV test proposed by Young (1999). Therefore, we estimate a multivariate second-stage regression containing several omitted and possibly correlated variables.[38] When applying this approach, we must include several conventional control variables to avoid significant coefficients on the applied omitted variables while this variation can actually be explained by the conventional EM control variables.

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[37] Peasnell et al. (2000) alternatively use decile-specific first-stage regressions and compare abnormal accruals for the extreme decile group with the remaining groups. While recognizing the problem with the test for extreme performance, this alternative test also lacks informative value, since assessment of abnormal accruals from the decile-specific regressions is hard without an unbiased benchmark.

[38] What is important, we assume that these variables could additionally help to separate non-discretionary and discretionary accrual parts.

Finally, we apply a test procedure suggested by Beatty and Liao (2014), who address the prediction power of EM proxies. Therefore, we estimate a univariate logit regression, with the respective discretionary LLP proxy as the independent variable and a dummy variable that captures SEC comment letters and/or restatements.

Altogether, we exercise the following steps for each of the presented models:

(1) We estimate first-stage regressions of:
   a. The models ***B1-B7***, models ***S1-S4*** and models ***D1-D4*** using OLS with two-way clustering at bank and year level (Petersen 2008; Gow et al. 2010).
   b. The models ***D1-D4*** using system GMM with Windmeijer correction (Windmeijer, 2005).

   We compare coefficients and goodness-of-fit tests for all models.

(2) We compute discretionary LLP for bank i in year t as the residual of each model for both estimation procedures.
(3) We construct the following samples for each of the discretionary LLP proxies:
   a. We randomly select 25% of the firm-year observations of the total sample and construct an indicator value ($PART_{it}$) that takes up the value of one if the observation has been selected; and zero otherwise.
   b. We select 1%, 5% or 10% of the firm-year observations of the total sample from the firm-years with extreme cash-flow performance and construct an indicator value ($PART_{it}$) that takes up the value of one if the observation has been selected; and zero otherwise.
(4) We estimate the following univariate regression for all models, with PART being defined as stated in (3)a. and (3)b.:

$$DLLP\_abs_{it}(DLLP_{it}) = \alpha + \beta PART_{it} + \varepsilon_i \qquad (9)$$

   Using OLS regressions with specially designed robust standard errors for heteroscedastic cases[39] and test whether coefficient β is significantly different from zero on conventional levels (0.10, 0.05 and 0.01 levels).

[39] We find significant heteroscedasticity in the sample, which is why we apply standard errors using the Davidson and MacKinnon (1993) method, which obtains more conservative results in cases of heteroscedastic models.

(5) We apply 10,000 iterations for steps (3)a. & (4).

(6) We estimate the following multivariate regression for all models using two-way clustering on the firm and year level (Petersen, 2008; Gow et al., 2010):

$$\begin{aligned} DLLP\_abs_{it}(DLLP_{it}) \\ &= \alpha + \beta_1\, LLP_{it-1}/TA_{it-1} + \beta_2 SIZE_{it} + \beta_3 EBTP_{it} \\ &+ \beta_4 CAPB_{it} + \beta_5\, \Delta GDP_{jt}/GDP_{jt-1} \\ &+ \beta_6\, \Delta UNEMP_{jt}/UNEMP_{jt-1} + \beta_7\, LLP_{it}/TA_{it-1} \\ &+ \beta_8 GROWTH_{it} + \beta_9 LOSS_{it} + \beta_{10} LOANINT_{it} \\ &+ \beta_{11} INCDIV_{it} + \beta_{12}\, CFO_{it-1}/TA_{it-1} \\ &+ \beta_{13}\, CFO_{it}/TA_{it-1} + \beta_{14}\, CFO_{it+1}/TA_{it-1} + \varepsilon_i \end{aligned} \tag{10}$$

With the dependent variable

a. Absolute discretionary LLP ($DLLP\_abs_{it}$).

b. Non-absolute discretionary LLP ($DLLP_{it}$).

(7) We estimate the following univariate regression for all models using a logit regression.

$$CRKQ_{it} = \alpha + \beta ARES_{it} + \varepsilon_i \tag{11}$$

The randomised PART variable should not represent any systematic EM, particularly when univariate regressions are run at a high frequency rate. We expect rejection rates of the null hypothesis of no influence of the PART variable in test statistics for coefficient β to be (not) significantly different from 10%, 5% respectively 1% when model specifications are (good) poor at a confidence interval of 90%, 95% respectively 99%. For the extreme performance PART variable, we assume significant coefficients on PART whenever financial performance drives the magnitude of the discretionary accrual component significantly.[40]

Concerning the multivariate omitted variable regressions, we use the approach proposed by Young (1999), modify it when necessary and use the signed and absolute discretionary LLP. Consequently, we include cash flow from operations as a first omitted and possibly correlated variable. Accruals function as accounting-based adjustments of cash flows to obtain an earnings proxy that captures fundamental firm performance more accurately (e.g. Ball and Shivakumar, 2006).

[40] As discussed earlier, this could indicate low quality models or actual EM in high-performance situations, e.g. models of high quality. We further discuss this issue when we present the results in section 4.3.

Dechow and Dichev (2002) show that when accruals quality is high, accruals' variation should capture performance measurement errors of cash flows. Dechow et al. (1995) and McNichols (2002) further show for the non-financial industry models that excluding cash-flow patterns can cause omitted variable problems. We therefore include lagged (CFO_{it-1}), current (CFO_{it}) and forward (CFO_{it+1}) cash-flow from operations as separate regressors to study whether these problems also arise in our financial industry models.[41] Young (1999) uses fixed asset intensity to capture the magnitude of the depreciation expense as one major accrual. We correspond with this idea and use banks' counterpart for the loan loss provision, e.g. loan intensity ($LOANINT_{it}$), as another omitted variable. The common banking literature (e.g. Stiroh, 2004; Stiroh and Rumble, 2006; Lepetit et al., 2008) further discusses income diversification ($INCDIV_{it}$), e.g. the ratio of interest to non-interest income, as one important proxy for the strategic alignment of the bank. Especially, we regard this omitted variable as a proxy for the significance of interest income and therefore the significance of the loan portfolio for the bank from an earnings perspective. Following Young (1999), we also integrate $GROWTH_{it}$, calculated as change in sales scaled by lagged total assets. Expanding banks experience growth in assets as well as liabilities. However, if this development is not overall symmetric, growth may influence the level of non-discretionary accruals disproportionately and therefore growth needs to be accounted for when modelling discretionary accruals. (e.g. Sloan, 1996; Young, 1999). While industry models account for the change in sales as growth measure, the banking industry models do not, which is why we include $GROWTH_{it}$ to study the necessity of consideration.

The set of control variables used in the regression is as follows. We add lagged and current total LLP to control for measurement errors that might still exist. $LOSS_{it}$ is an indicator variable that takes on the value of one if the net income before extraordinary items of the firm i is negative in year t, and zero otherwise. It captures

[41] Even though the relationship between cash flows and earnings might be less direct and intuitive within banks, accruals should also be means of providing a more accurate performance measure, hence the inclusion of the operating cash-flow variables should be able to describe non-discretionary loan loss provisioning variation. E.g., consider the case of a bank with a high-risk loan portfolio that reports high operating cash flows in the first year of observation. Here, high loan loss provisioning will appropriately counter-steer to provide a smoothed earnings number, while operating cash flows might deteriorate in the following years as high-risk loans are charged off. On a final note, LLP might have a rather forward-looking impact; hence, cash flows in year t+2 or t+3 could be appropriate alternative variables to map the mechanism of provisioning accruals.

the differences in EM incentives when earnings are below or above zero. Once again, we incorporate the controls for macroeconomic effects ΔGDP_{jt} and $\Delta UNEMP_{jt}$.

The test procedure by Beatty and Liao (2014) studies prediction power as another desirable property of functional EM proxies. If our discretionary LLP proxies are well fitted, they should be highly correlated with the actual amount of EM. Consequently, if a proxy is able to predict actual EM more reliably than another proxy, it can be considered as superior. Due to the lacking observability of actual EM, we employ a proxy for suspected or detected, and therefore highly likely EM. Since 2005, the SEC publicly releases correspondence between SEC staff and SEC filers that can be retrieved through the EDGAR database. In these comment letters, the SEC staff comments, criticises and requests more or altered information regarding disclosures. Following Beatty and Liao (2014), we construct a dummy variable $CRKQ_{it}$, which equals one if:

a. The bank received an SEC comment letter regarding their annual (K-10) or quarterly (Q-10) earnings report due to unappropriated handling of LLP, or
b. The bank restated their annual (K-10) or quarterly (Q-10) earnings report due to reasons connected to the handling of LLP,

and zero otherwise.[42] We then estimate a univariate logit regression with the average absolute discretionary LLP as the dependent variable. Based on the resulting coefficients, we calculate probabilities. If the resulting probability is above 50%, the model assumes actual EM and expects a detection by the SEC, while probabilities below 50% are interpreted as the absence of actual EM.

3.3.5 Methodology

We estimate first-stage regressions using two different estimation procedures. We then use the estimated coefficients to calculate respective residuals of the models for each observation, representing our EM proxies (abnormal/discretionary LLP). To estimate the seven basic models, four static and four dynamic models, we use OLS with standard errors based on two-way clustering on the year- and bank-level

[42] Consequently, CRKQ separates the sample into banks with a high probability of EM in the financial year and banks, which do not or considerably less engage in EM.

(e.g. Petersen, 2008; Gow et al., 2010). For the four dynamic models, we alternatively follow prior banking literature with dynamic settings and use system GMM (e.g. Arellano and Bover, 1995; Blundell and Bond, 1998). We apply all available lags as GMM-style instruments for the lagged dependent variable LLP_{it-1}, while all remaining variables are considered as strictly exogenous.[43] Since standard errors are downward biased in a non-asymptotic setting (e.g., $T \rightarrow \infty$ is not given), and significances therefore overconfident, we apply the standard error correction for finite sample panels developed by Windmeijer (2005).

For models ***B1-B7*** as well as models ***S1-S4*** and ***D1-D4*** using OLS with two-way clustering, we report R^2, adjusted R^2 and Bayesian Information Criterion (BIC) as tests for absolute and relative goodness-of-fit. Higher R^2 (respectively adjusted R^2) values indicate a higher explanatory power of the model and therefore a higher proportion of variation of non-discretionary LLP being explained, leading to lower volatility and therefore more conservatism in our discretionary LLP proxy, which can limit type I errors.[44] Lower BIC values indicate a higher predictive power of the model. Schwarz (1978) introduces the BIC as an extension of the Akaike Information Criterion, assigning different weights to the penalties for the inclusion of additional variables based on the natural logarithm of the number of observations for nested and non-nested models. Given our models that are highly nested in each other, BIC allows us to determine the model with the highest likelihood of generating the underlying data (e.g. Raftery, 1995).[45] For the system GMM estimator, we alternatively report AR (1), AR (2) and Hansen statistics as goodness-of-fit tests. They should be significant for AR (1), respectively insignificant on a 10% level for AR (2) and Hansen statistics. These thresholds should not be exceeded to obtain valid regressions and interpretable coefficients.

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[43] Bouvatier et al. (2014) also use this assumption in their analysis. Any different approach would contradict the OLS assumptions of exogeneity between dependent and independent variables and question appropriateness of OLS for the remaining models.

[44] We note that this is no clear indication of a better model, although it is likely that regressors, which marginally increase the explanation of the variation in the dependent variable, enhance the modelling until a certain degree of overall explanatory power, since it is highly unlikely that high degrees of total LLP are systematically driven by discretion. Nevertheless, we build our conclusions on various additional tests and not only on the R^2 of the first-stage regressions.

[45] Decisively, we do not seek to explain 100% of the variation in total LLP, but the non-discretionary part. This is why we analyse actual prediction rates for situations of highly likely use of EM in section 4.5.

3.4 Results

3.4.1 Descriptive Statistics

Table 3.3 contains descriptive statistics for all relevant variables. Banks in our sample on average provision an amount 0.47 percent of the lagged total assets, while mean non-performing loans are 2 percent of the lagged total assets. The loan portfolios of the banks represent on average 70.61 percent of the beginning of the year total assets, while variation is low with an interquartile range of only 18.01 percent. Mean net charge-offs and non-performing loans of 0.3559 and 0.02 together with a standard deviation of 2.2729 and 0.0215 imply that few extreme observations drive the mean.[46] A mean allowance for loan losses of 1.1 percent compared to mean non-performing loans of 2.0 percent imply that on average banks might be in a situation where building up allowances is an issue.

Table 3.4 shows pairwise correlation matrices for the relevant variables. We find no unexpectedly high correlations that would imply multicollinearity issues that would lead to implausible or noisy parameter estimates (e.g. O'Brien 2007).

We also study mean variance inflation factors and find that they are considerably below 5 for all specifications.[47] Furthermore, we find expected correlations between our non-discretionary variables and LLP. Interestingly, we find a positive and significant correlation between beginning of the year loan loss allowances and LLP, which could stand for a situation of increasing reserves and loss recognition, which results in even higher provisioning.

[46] We note that few banks exist, which account for considerable net-charge offs and run into financial distress in the following year, especially throughout years of the financial crisis. However, our results do not change when we alternatively exclude these observations.

[47] A mean variance inflation factor of 5.01 for model ***B1*** could indicate minor multicollinearity problems with this model. However, we follow O'Brien (2007), who extensively discusses the issue of multicollinearity and assesses rules of thumb, in particular a VIF of 10 and above. Altogether, multicollinearity values below 10 should not indicate a crucial problem in our analysis.

Table 3.3

Descriptive statistics of relevant variables

	Mean	$\boldsymbol{Q_{50}}$	**Std. Dev.**	$\boldsymbol{Q_{25}}$	$\boldsymbol{Q_{75}}$
Basic specification patterns					
LLP_{it}	0.0047	0.0024	0.0071	0.0009	0.0057
NPA_{it-1}	0.0200	0.0136	0.0215	0.0062	0.0254
ΔNPA_{it}	0.0013	0.0000	0.0136	-0.0039	0.0049
ALW_{it-1}	0.0110	0.0097	0.0060	0.0073	0.0132
TL_{it}	0.7061	0.7001	0.1606	0.6126	0.7927
ΔTL_{it}	0.0454	0.0309	0.1079	-0.0069	0.0737
NCO_{it}	0.3559	0.0020	2.2729	0.0005	0.0067
Set of further control variables					
$SIZE_{it}$	14.4496	14.1297	1.5724	13.3686	15.2051
$EBTP_{it}$	0.0133	0.0138	0.0088	0.0094	0.0177
$CAPB_{it}$	0.0986	0.0948	0.0258	0.0837	0.1088
Macroeconomic control variables					
ΔGDP_{jt}	0.0308	0.0378	0.0184	0.0314	0.0411
$\Delta UNEMP_{jt}$	0.0190	-0.0889	0.2187	-0.0976	0.0319
OMV variables					
CFO_{it}	0.0126	0.0136	0.0292	0.0089	0.0181
$Growth_{it}$	0.0005	-0.0005	0.0088	-0.0033	0.0031
$LOSS_{it}$	0.1348	0.0000	0.3416	0.0000	0.0000
$LOANINT_{it}$	0.6608	0.6760	0.1176	0.5990	0.7431
$INCDIV_{it}$	0.2677	0.2141	0.2360	0.1296	0.3291

All variables are defined in Appendix 3.A.

Table 3.4

Correlations of regressors of the basic, static and dynamic models

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1.	LLP_{it}	1							
2.	NPA_{it-1}	0.3122***	1						
3.	ΔNPA_{it}	0.3227***	-0.3298***	1					
4.	ALW_{it-1}	0.3031***	0.5944***	-0.1937***	1				
5.	TL_{it}	0.0750***	-0.1068***	0.1820***	0.0320	1			
6.	ΔTL_{it}	-0.2041***	-0.3229***	0.1047***	-0.2455***	0.6942***	1		
7.	NCO_{it}	0.0054	-0.0182	0.1210***	-0.0616***	-0.0181	0.0133	1	
8.	$SIZE_{it}$	-0.0155	-0.1026***	-0.0705***	0.0440*	-0.0358	0.1129***	-0.1379***	1
9	$EBTP_{it}$	-0.1578***	-0.2612***	-0.0015	-0.0747***	0.1706***	0.2271***	-0.0699***	0.2703***
10	$CAPB_{it}$	-0.1543***	0.0147	-0.1187***	0.0679***	-0.0345	-0.0603***	-0.0385*	-0.1437***
11	ΔGDP_{it}	-0.3440***	0.0802***	-0.3430***	0.0840***	-0.0398*	0.0861***	-0.1008***	0.0956***
12	$\Delta UNEMP_{it}$	0.4018***	-0.1206***	0.4067***	-0.116***	0.0600***	-0.1012***	0.1400***	-0.1612***
		9	**10**	**11**	**12**				
9.	$EBTP_{it}$	1							
10	$CAPB_{it}$	0.1090***	1						
11.	ΔGDP_{it}	0.1111***	0.0413*	1					
12.	$\Delta UNEMP_{it}$	-0.1107***	-0.0745***	-0.9342***	1				

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All variables are defined in Appendix 3.A.

Tables 3.5 and 3.6 show signed and absolute discretionary LLP from our models. Signed values are not statistically different from zero on the 0.01 level, indicating that none of our models produces EM proxies with systematic upward or downward bias.[48] Mean Absolute discretionary LLP and standard deviations are considerably different for all models, particularly when system GMM is applied for model ***D2*** and ***D4*** compared to corresponding regressions using two-way clustering. Discretionary LLP from models ***D2*** and ***D4*** with two-way clustering account for the lowest mean values and standard deviations, hence the most conservative proxies.

Table 3.5

Descriptive statistics of the signed value of discretionary loan loss provisions (DLLP)

	Mean	Q_{50}	Std. Dev.	Q_{25}	Q_{75}
First-stage OLS					
B1	0.0000	-0.0011	0.0061	-0.0032	0.0015
B2	0.0000	-0.0005	0.0054	-0.0026	0.0015
B3	0.0000	-0.0006	0.0058	-0.0030	0.0018
B4	0.0000	-0.0011	0.0061	-0.0032	0.0016
B5	0.0000	-0.0004	0.0053	-0.0025	0.0017
B6	0.0000	-0.0006	0.0058	-0.0030	0.0018
B7	0.0000	-0.0005	0.0054	-0.0026	0.0016
S1	0.0000	-0.0004	0.0053	-0.0025	0.0016
S2	0.0000	-0.0004	0.0052	-0.0026	0.0016
S3	0.0000	-0.0004	0.0052	-0.0024	0.0015
S4	0.0000	-0.0004	0.0051	-0.0025	0.0016
D1	0.0000	-0.0003	0.0050	-0.0020	0.0013
D2	0.0000	-0.0003	0.0049	-0.0021	0.0014
D3	0.0000	-0.0003	0.0049	-0.0020	0.0012
D4	0.0000	-0.0003	0.0048	-0.0021	0.0012
First-stage GMM					
D1	0.0001	0.0000	0.0053	-0.0017	0.0017
D2	0.0000	-0.0008	0.0083	-0.0047	0.0037
D3	0.0002	-0.0001	0.0058	-0.0028	0.0024
D4	0.0001	-0.0008	0.0079	-0.0046	0.0036

$DLLP$ is the signed value of the residual from the respective first-stage regression. All variables are defined in Appendix 3.A.

[48] We apply untabulated univariate tests to address this issue. They confirm this favorable setting for all discretionary proxies.

Table 3.6

Descriptive statistics of the absolute value of discretionary loan loss provisions (DLLP_abs)

	Mean	Q_{50}	**Std. Dev.**	Q_{25}	Q_{75}
First-stage OLS					
B1	0.0039	0.0026	0.0047	0.0012	0.0050
B2	0.0034	0.0021	0.0043	0.0010	0.0041
B3	0.0037	0.0024	0.0045	0.0011	0.0048
B4	0.0039	0.0026	0.0047	0.0012	0.0049
B5	0.0033	0.0021	0.0042	0.0010	0.0041
B6	0.0037	0.0024	0.0045	0.0011	0.0047
B7	0.0033	0.0021	0.0042	0.0009	0.0041
S1	0.0033	0.0021	0.0042	0.0010	0.0041
S2	0.0033	0.0022	0.0040	0.0010	0.0040
S3	0.0032	0.0020	0.0041	0.0009	0.0039
S4	0.0032	0.0021	0.0040	0.0009	0.0039
D1	0.0029	0.0017	0.0040	0.0007	0.0034
D2	0.0029	0.0018	0.0039	0.0008	0.0033
D3	0.0028	0.0016	0.0040	0.0007	0.0033
D4	0.0028	0.0017	0.0039	0.0007	0.0032
First-stage GMM					
D1	0.0031	0.0017	0.0043	0.0008	0.0034
D2	0.0059	0.0043	0.0058	0.0022	0.0077
D3	0.0038	0.0026	0.0044	0.0012	0.0048
D4	0.0056	0.0041	0.0055	0.0021	0.0072

$DLLP\_abs$ is the absolute value of the residual from the respective first-stage regression. All variables are defined in Appendix 3.A.

3.4.2 First-stage regression results

Tables 3.7 – 3.9 show first-stage regressions of Eq. (1)-(3). We start analysing the basic models, since they entail concise specifications, from where on all other models derive. To assess the absolute and relative goodness-of-fit of our models, we use adjusted r-squared and the BIC.[49] Results in table 3.7 indicate for models ***B1-B7*** that all regressors exert a significant influence on total LLP except for NCO_{it} and ΔGDP_{it}, which are only marginally significant in one case each. The signs for the coefficients are as expected, while the coefficient on ALW_{it-1} is positive and significant for models ***B3***, ***B5*** and ***B6***. This result is in line with our univariate findings and the proposition that higher lagged loan loss reserves are associated with higher loss recognition, leading to higher provisioning in the current year.

[49] We use adjusted r-squared instead of r-squared, since it corrects for the degrees of freedom, while r-squared increases with the inclusion of every new regressor.

Table 3.7

First stage multiple regressions for basic models B1-B7

Dependent variable: total loan loss provisions (LLP)

$$LLP_{it}/TA_{it-1} = \alpha_0\{+\beta_1 NPA_{it-1}/TA_{it-1} + \beta_2 \Delta NPA_{it}/TA_{it-1}\}[+\beta_3 ALW_{it-1}/TA_{it-1}] + \beta_4 TL_{it}/TA_{it-1} + \beta_5 \Delta TL_{it}/TA_{it-1} (+\beta_6 NCO_{it}/TA_{it-1}) + \beta_7 \Delta GDP_{jt}/GDP_{jt-1} + \beta_8 \Delta UNEMP_{jt}/UNEMP_{jt-1} + \varepsilon_{it}$$

	B1	***B2***	***B3***	***B4***	***B5***	***B6***	***B7***
NPA_{it-1}		0.137			0.108		0.139
		(5.65)***			(7.30)***		(5.59)***
ΔNPA_{it}		0.168			0.168		0.171
		(4.18)***			(4.28)***		(4.19)***
ALW_{it-1}			0.351		0.207	0.351	
			(3.06)***		(2.15)**	(3.05)***	
TL_{it}	0.014	0.008	0.008	0.014	0.005	0.008	0.007
	(3.04)***	(2.79)***	(2.96)***	(3.08)***	(2.61)***	(3.01)***	(2.96)***
ΔTL_{it}	-0.026	-0.013	-0.014	-0.025	-0.009	-0.014	-0.012
	(2.51)**	(1.97)**	(2.30)**	(2.52)**	(1.72)*	(2.31)**	(1.98)**
NCO_{it}				-0.000		-0.000	-0.000
				(1.30)		(1.37)	(1.73)*
ΔGDP_{it}	0.069	0.086	0.101	0.072	0.094	0.105	0.093
	(0.61)	(1.52)	(1.22)	(0.64)	(1.86)*	(1.24)	(1.59)
$\Delta UNEMP_{it}$	0.016	0.016	0.021	0.017	0.017	0.021	0.017
	(1.83)*	(3.30)***	(3.16)***	(1.84)*	(3.97)***	(3.15)***	(3.34)***
$cons$	-0.007	-0.006	-0.008	-0.007	-0.006	-0.008	-0.006
	(1.48)	(2.32)**	(2.07)**	(1.49)	(2.61)***	(2.07)**	(2.38)**
R^2	0.25	0.41	0.32	0.25	0.43	0.32	0.42
R^2_{adj}	0.25	0.41	0.32	0.25	0.43	0.32	0.41
BIC	-13,595	-14,032	-13,772	-13,591	-14,082	-13,768	-14,047
F	89.02	85.96	91.05	71.37	80.36	76.11	75.63
N	1,854	1,854	1,854	1,854	1,854	1,854	1,854

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using two-way clustering at the firm and year level (e.g. Petersen 2008; Gow et al. 2010). We apply the BIC with correction for N (e.g. Schwarz 1978) to assess the relative fit of our models and follow Raftery (1995) in assessment. All variables are defined in Appendix 3.A.

Concerning the absolute goodness-of-fit, the highest increase in r-squared is achieved by incorporating the non-performing asset pattern group (increase in R^2_{adj} by 0.16), followed by the inclusion of ALW_{it-1} (increase in R^2_{adj} by 0.07), while adding NCO_{it} leaves an insignificant coefficient and hence no increase in explanatory power. What is more, the mutual use of both NPA and ALW patterns (model ***B5***) results only in a slight improvement in R^2_{adj} compared to model ***B2***. Hence, loan loss allowances and non-performing assets seem to explain equal amounts of variation in total LLP.[50] Taking a closer look at the relative goodness-of-fit, the general results prevail, while the application of BIC unfolds more details. Given the guidelines for evidence in Raftery (1995)[51], model ***B4*** is positively inferior in comparison to model ***B1***, while model ***B7*** outperforms model ***B2*** very strongly. This result still leaves the sole inclusion of our NCO pattern with a loss of

[50] In particular, both the coefficients on NPA_{it-1} and ALW_{it-1}, decrease when they are mutually included, representing an adjustment of the reserves based on current non-performing assets.

[51] Raftery (1995) proposes absolute differences from 0-2 as weak, 2-6 as positive, 6-10 as strong and >10 as very strong evidence of preferral of a model in goodness-of-fit.

fit. However, the mutual use of the NCO pattern and the NPA pattern group strongly indicates a better fit compared to the sole use of NPA, which has not been detected by R_{adj}^2. Even more, compared to absolute goodness-of-fit, we find very strong evidence (BIC difference of 50.49) that there is a better fit of model ***B5*** relative to ***B2***, suggesting that even though NPA pattern groups are already in use, the addition of loan loss allowance patterns can enhance the fit of the model. Consequently, while NPA always seem to increase the fit of our models, loan loss allowances might work as an alternative, while net charge-offs only improve our modelling if they are used together with NPA patterns.[52]

Given these results, model ***S1*** in table 3.8 is of major interest, because it includes NCO, ALW and NPA patterns. The significant coefficients for all three pattern groups demonstrate that integrating NCO_{it} can have a considerable effect if used in addition to loan loss allowances and non-performing assets. ALW_{it-1} is again positive and significant for models ***S1***-***S4***. While R_{adj}^2 does not imply any significant difference between modelling without NCO (model ***B5***) and model ***S1***, the difference in BIC shows very strong evidence for a better fit of ***S1***. Model ***S3*** contains further lagged and forward components of non-performing assets. We observe that these exert only marginal increases in explanatory power, while researchers will have to trade-off a further loss of two panel years. However, relative goodness-of-fit testing shows a difference in BIC that is considerable. The further set of control variables ($SIZE_{it}$, $EBTP_{it}$ and $CAPB_{it}$) likewise explains considerable variation in total LLP, while model ***S4*** contains all static regressors and yields an adjusted r-squared of 0.47, which is the highest explanatory power of the static models. The results on the information criterion are in line, with a difference in BIC between model ***S1*** and ***S4*** of 99.83.

[52] Furthermore, the use of net charge-off patterns seems to decrease the fit of the model when we use them together with loan loss allowance patterns, as indicated by a positive evidence for the difference in BIC between model ***B3*** and ***B6***.

Table 3.8

First stage multiple regressions for the static models S1-S4 and dynamic models D1-D4 using two-way clustering

Dependent variable: total loan loss provisions (LLP)

$$LLP_{it}/TA_{it-1} = \alpha_0 + \beta_1 NPA_{it-1}/TA_{it-1} + \beta_2 \Delta NPA_{it}/TA_{it-1} + \beta_3 ALW_{it-1}/TA_{it-1} + \beta_4 TL_{it}/TA_{it-1} + \beta_5 \Delta TL_{it}/TA_{it-1} + \beta_6 NCO_{it}/TA_{it-1} + \beta_7 \Delta GDP_{jt}/GDP_{jt-1} + \beta_8 \Delta UNEMP_{jt}/UNEMP_{jt-1} \{+\beta_9 SIZE_{it} + \beta_{10} EBTP_{it}/TA_{it-1} + \beta_{11} CAPB_{it}\} [+\beta_{12} NPA_{it-2}/TA_{it-1} + \beta_{13} \Delta NPA_{it+1}/TA_{it-1}] + \beta_{14} LLP_{it-1}/TA_{it-1} + \varepsilon_{it}$$

	S1	***S2***	***S3***	***S4***	***D1***	***D2***	***D3***	***D4***
NPA_{it-1}	0.110	0.110	0.163	0.157	0.072	0.075	0.117	0.115
	(7.50)***	(7.41)***	(8.70)***	(8.02)***	(5.94)***	(5.97)***	(5.66)***	(5.48)***
ΔNPA_{it}	0.171	0.165	0.158	0.153	0.159	0.155	0.150	0.147
	(4.28)***	(4.28)***	(4.21)***	(4.17)***	(3.84)***	(3.85)***	(3.79)***	(3.78)***
ALW_{it-1}	0.204	0.189	0.251	0.236	-0.014	-0.014	0.032	0.031
	(2.16)**	(2.36)**	(2.75)***	(3.09)***	(0.34)	(0.33)	(0.81)	(0.80)
TL_{it}	0.005	0.006	0.004	0.006	0.005	0.006	0.005	0.006
	(2.70)***	(3.01)***	(2.30)**	(2.66)***	(2.77)***	(2.91)***	(2.33)**	(2.54)**
ΔTL_{it}	-0.009	-0.011	-0.008	-0.010	-0.006	-0.008	-0.005	-0.007
	(1.69)*	(2.11)**	(1.60)	(2.02)**	(1.20)	(1.55)	(1.13)	(1.46)
NCO_{it}	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(1.76)*	(1.50)	(1.87)*	(1.65)*	(2.10)**	(1.82)*	(2.20)**	(1.96)*
ΔGDP_{it}	0.101	0.110	0.076	0.087	0.053	0.063	0.031	0.041
	(1.92)*	(2.21)**	(1.63)	(1.90)*	(1.50)	(2.09)**	(0.89)	(1.37)
$\Delta UNEMP_{it}$	0.018	0.019	0.015	0.016	0.013	0.014	0.010	0.011
	(3.98)***	(4.49)***	(3.49)***	(3.96)***	(3.65)***	(4.70)***	(2.91)***	(3.79)***
$SIZE_{it}$		0.001		0.000		0.000		0.000
		(2.00)**		(1.82)*		(1.92)*		(1.73)*
$EBTP_{it}$		-0.030		-0.041		-0.024		-0.032
		(1.01)		(1.45)		(0.88)		(1.22)
$CAPB_{it}$		-0.024		-0.022		-0.018		-0.017
		(3.49)***		(3.33)***		(4.46)***		(4.37)***
NPA_{it-2}			-0.080	-0.074			-0.061	-0.057
			(5.92)***	(5.57)***			(3.95)***	(3.46)***
ΔNPA_{it+1}			-0.001	-0.001			0.011	0.011
			(0.06)	(0.03)			(0.66)	(0.63)
LLP_{it-1}					0.379	0.358	0.363	0.344
					(7.37)***	(8.03)***	(6.60)***	(6.93)***
$cons$	-0.006	-0.012	-0.005	-0.010	-0.004	-0.009	-0.003	-0.007
	(2.69)***	(2.17)**	(2.56)**	(1.95)*	(2.57)**	(2.14)**	(2.04)**	(1.81)*
R^2	0.43	0.46	0.45	0.47	0.51	0.52	0.52	0.53
R^2_{adj}	0.43	0.45	0.45	0.47	0.50	0.52	0.51	0.53
BIC	-14,096	-14,149	-14,151	-14,196	-14,368	-14,412	-14,411	-14,443
F	71.76	57.90	60.89	52.80	76.48	64.10	64.44	57.54
N	1,854	1,854	1,854	1,854	1,854	1,854	1,854	1,854

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using two-way clustering at the firm and year level (e.g. Petersen 2008; Gow et al. 2010). We apply the BIC with correction for N (e.g. Schwarz 1978) to assess the relative fit of our models and follow Raftery (1995) in assessment. All variables are defined in Appendix 3.A.

Starting with model ***D1***, the conversion to a dynamic approach expands explanatory power to a level of 0.50 with a very strong evidence of a mutual increase of relative fit. Again, the use of controls and/or non-performing loan regressors has slightly positive effects (R^2_{adj} between 0.51 and 0.53). These results are again supported by a look at the relative goodness-of-fit. What is important, ALW_{it-1} turns insignificant for the dynamic versions ***D1***-***D4***, while LLP_{it-1} is highly significant. We remark that the effect of loan loss reserves is mainly driven by last year's addition to the reserve, e.g., LLP_{it-1}.

Altogether, these results show that non-performing assets are by far the most important pattern group when it comes to modelling EM proxies. The effect of NCO seems to be highly dependent on the ex-ante specification, while the omission of this pattern has no influence on the explanatory power and leads to the lowest decrease in relative goodness-of-fit (difference in BIC between model ***S1*** and ***B5*** of 13.72). Additional lag and forward patterns of the NPA pattern group and/or the additional set of controls significantly improve the BIC, while explanatory power only increases by 2%. However, the switch to a dynamic model yield a much higher increase in both explanatory power (6-7% compared to the respective static model) and BIC (up to a difference of BIC of 272.06). Therefore, EM studies should consider the trade-off between more lags/forwards of NPA patterns and the loss in number of observations, while dynamic models should normally entail insignificant losses of observations.

For the dynamic models ***D1-D4*** with alternative system GMM estimation, we apply instrument settings that cancel out issues of over-identifying restrictions, which gives us a certain fit of the models. However, standard goodness-of-fit tests (R^2_{adj}, BIC) do not exist. We alternatively compare coefficients of the models, which leaves us with marginal or no significances for the loans and net charge-off pattern groups. As expected, LLP_{it-1} has a highly significant influence on the magnitude on the variation of current LLP, as long as we do not include the additional set of control variables. Furthermore, the coefficient on ALW_{it-1} is negative and significant in these models (***D1*** & ***D3***). While this result could challenge our univariate results for ALW_{it-1} as well as the static first-stage regressions, we note that in the case of ALW_{it-1} and LLP_{it-1} capturing similar or identical effects, the sum of the coefficients in our dynamic system GMM models ***D1*** and ***D3*** again shows an overall positive effect of past provisioning.

Table 3.9

First stage regressions for the dynamic models using system GMM

Dependent variable: total loan loss provisions (LLP)

$$LLP_{it}/TA_{it-1} = \alpha_0 + \beta_1\, NPA_{it-1}/TA_{it-1} + \beta_2\, \Delta NPA_{it}/TA_{it-1} + \beta_3\, ALW_{it-1}/TA_{it-1} + \beta_4\, TL_{it}/TA_{it-1} + \beta_5\, \Delta TL_{it}/TA_{it-1} + \beta_6\, NCO_{it}/TA_{it-1} + \beta_7\, \Delta GDP_{jt}/GDP_{jt-1} + \beta_8\, \Delta UNEMP_{jt}/UNEMP_{jt-1}\ \{+\beta_9 SIZE_{it} + \beta_{10}\, EBTP_{it}/TA_{it-1} + \beta_{11} CAPB_{it}\}\ [+\beta_{12}\, NPA_{it-2}/TA_{it-1} + \beta_{13}\, \Delta NPA_{it+1}/TA_{it-1}]\ + \beta_{14}\, LLP_{it-1}/TA_{it-1} + \varepsilon_{it}$$

	D1	**D2**	**D3**	**D4**
NPA_{it-1}	0.150	0.183	0.057	0.167
	(4.93)***	(4.74)***	(1.07)	(2.32)**
ΔNPA_{it}	0.270	0.276	0.175	0.254
	(4.97)***	(3.95)***	(2.51)**	(3.54)***
ALW_{it-1}	-0.227	-0.191	-0.348	-0.210
	(2.81)***	(1.44)	(2.13)**	(0.93)
TL_{it}	0.006	0.015	0.022	0.017
	(0.68)	(1.38)	(1.58)	(1.13)
ΔTL_{it}	-0.005	-0.024	-0.019	-0.026
	(0.62)	(1.96)*	(1.32)	(1.75)*
NCO_{it}	-0.000	0.000	-0.000	0.000
	(0.88)	(0.76)	(0.43)	(0.71)
ΔGDP_{jt}	0.043	0.038	0.111	0.049
	(1.95)*	(0.88)	(1.84)*	(0.80)
$\Delta UNEMP_{jt}$	0.009	0.008	0.017	0.010
	(3.71)***	(1.73)*	(2.38)**	(1.40)
$SIZE_{it}$		0.002		0.002
		(2.28)**		(2.06)**
$EBTP_{it}$		0.082		0.066
		(0.67)		(0.55)
$CAPB_{it}$		-0.234		-0.212
		(1.98)**		(1.72)*
NPA_{it-2}			0.049	-0.003
			(0.74)	(0.04)
ΔNPA_{it+1}			-0.151	-0.029
			(1.44)	(0.27)
LLP_{it-1}	0.416	0.205	0.439	0.234
	(4.68)***	(1.68)*	(3.83)***	(1.43)
$cons$	-0.004	-0.015	-0.014	-0.019
	(0.77)	(0.85)	(1.79)*	(0.92)
Chi^2	474.64	272.84	354.90	343.71
$Ar1$	-4.08	-3.49	-4.14	-2.76
$Ar2$	-0.03	-1.60	0.67	-0.90
$Hansen$	39.66	26.83	33.62	27.91
J	42.00	42.00	42.00	42.00
N_G	430	430	430	430
N	1,854	1,854	1,854	1,854

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using system-GMM (e.g. Arellano and Bover 1995; Blundell and Bond 1998) with all available lags as GMM-style instruments for LLP_{it-1} and Windmeijer (2005) correction, while all remaining variables are considered as strictly exogenous. All variables are defined in Appendix 3.A.

3.4.3 Univariate Analysis on Measurement Errors

Table 3.10 contains results for the univariate regressions of the EM proxies on our randomized PART variable. For each of the models, we report the frequency of significant β_1 coefficients when we alternatively apply confidence intervals of 1%, 5% and 10%. The frequencies are within the thresholds, e.g. not significantly different from the frequencies you would expect at random. We conclude that the Gaussian assumptions are not violated and we have no biases in this regard.

Table 3.10 PART – randomly selected indicator				
Dependent variable: signed discretionary loan loss provisions ($DLLP$) $DLLP_{it} = \alpha + \beta PART_{it} + \varepsilon_i$				
	B1	**B2**	**B3**	**B4**
10% level	954	966	1081	1032
5% level	510	501	529	571
1% level	138	122	107	137
	B5	**B6**	**B7**	
10% level	1032	1044	1023	
5% level	541	541	539	
1% level	118	118	120	
	S1	**S2**	**S3**	**S4**
10% level	1021	984	1055	1026
5% level	521	501	530	538
1% level	115	122	124	112
	D1	**D2**	**D3**	**D4**
10% level	1030	1001	1000	1029
5% level	510	533	537	548
1% level	121	123	132	116
	D1 (GMM)	**D2 (GMM)**	**D3 (GMM)**	**D4 (GMM)**
10% level	999	1006	991	1039
5% level	502	537	477	513
1% level	129	113	118	96

* Indicate whether the number of occurrence of significant coefficients on PART for 10,000 replications of the univariate regression is lower than the hypothesised number. All variables are defined in Appendix 3.A.

Table 3.11 reports the results for the univariate regression, in which the PART variable represents extreme CFO performance. We find significant coefficients, especially on the 10% and 5% levels. These results could indicate that our EM proxies are biased with regard to extreme CFO performance. If this holds, the applied EM models are not able to unambiguously separate non-discretionary performance influences from discretionary LLP. However, as mentioned earlier, this test can be biased due to EM taking place in observations with extreme CFO performance, e.g., over- or under-provisioning. If this holds, the separation works well and the significant coefficient is the result of successful modelling. In particular, when adding a set of further controls, we include $EBTP_{it}$ as performance before provisioning, while the results on this univariate test do not change.[53]

[53] We further study the influence of cash flow performance in our multivariate analysis in section 4.4.

Table 3.11
PART – extreme performance indicator (CFO)

Dependent variable: signed discretionary loan loss provisions ($DLLP$)

$$DLLP_{it} = \alpha + \beta PART_{it} + \varepsilon_i$$

	B1	**B2**	**B3**	**B4**
10% selected	(4.07)***	(4.90)***	(3.78)***	(4.06)***
5% selected	(3.05)***	(3.90)***	(2.94)***	(3.13)***
1% selected	(1.44)	(1.69)*	(1.19)	(1.46)
	B5	**B6**	**B7**	
10% selected	(4.29)***	(3.74)***	(4.75)***	
5% selected	(3.65)***	(2.99)***	(3.84)***	
1% selected	(1.54)	(1.20)	(1.72)*	
	S1	**S2**	**S3**	**S4**
10% selected	(4.13)***	(4.70)***	(4.01)***	(4.41)***
5% selected	(3.58)***	(4.02)***	(3.69)***	(3.90)***
1% selected	(1.56)	(1.81)*	(1.56)	(1.60)
	D1	**D2**	**D3**	**D4**
10% selected	(3.68)***	(4.21)***	(3.76)***	(4.36)***
5% selected	(3.39)***	(3.78)***	(3.42)***	(3.79)***
1% selected	(1.74)*	(1.85)*	(1.67)*	(1.73)*
	D1 (GMM)	**D2 (GMM)**	**D3 (GMM)**	**D4 (GMM)**
10% selected	(4.32)***	(3.16)***	(4.27)***	(3.33)***
5% selected	(3.59)***	(2.49)**	(3.71)***	(2.61)***
1% selected	(1.71)*	(0.32)	(1.50)	(0.49)

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. Variables are defined in Appendix 3.A.

3.4.4 Multivariate Analysis on Omitted Variables

Tables 3.12, 3.14 and 3.16 contain multivariate regressions of the signed discretionary LLP on omitted variables for all models.[54] We use the regressions on signed discretionary LLP to study probable non-linearity issues of variables that have been included in the first stage. In table 3.14, we find significant coefficients for the further set of controls for size, performance and capital requirements. What is important, these show opposing signs compared to the first-stage results in table 3.7. Assuming that an inclusion of these regressors should show no significances in the second stage whenever there is a linear relationship, we propose a non-linear fit of the data for these control variables.[55] However, results on absolute discretionary LLP (table 3.15) show no significant coefficients on size and capital requirement, while the coefficients on $EBTP_{it}$ are significant and negative, indicating pro-cyclical bank provisioning behaviour. Therefore, studies following two-step approaches might consider either non-linear modelling or additional control on the second stage, while one-step approaches are only left with the former solution. The outcomes on LLP_{it-1}, ΔGDP_{jt} and $\Delta UNEMP_{jt}$ also indicate non-linearity (for all

[54] Compared to our first-stage regressions, we lose one observation each for $GROWTH_{it}$, CFO_{it} and CFO_{it-1} due to data insufficiency, which gives us a sample of 1,851 firm-years.

[55] We run simple curve estimations to test this proposition. They show for the respective signed discretionary LLP that common non-linear formulations (e.g., squared or cubic) fit the data significantly better than a linear model.

models in tables 3.14-3.16), hence we suggest an equivalent strategy to address this issue.

Table 3.12
Multivariate regressions to study omitted correlated variables in basic models B1-B7

Dependent variable: signed value of discretionary loan loss provisions ($DLLP$)

$$DLLP_{it} = \alpha + \beta_1 LLP_{it-1} + \beta_2 SIZE_{it} + \beta_3 EBTP_{it} + \beta_4 CAPB_{it} + \beta_5 \Delta UNEMP_{it} + \beta_6 \Delta GDP_{it} + \beta_7 LLP_{it} + \beta_8 GROWTH_{it} + \beta_9 LOSS_{it} + \beta_{10} LOANINT_{it} + \beta_{11} INCDIV_{it} + \beta_{12} CFO_{it-1} + \beta_{13} CFO_{it} + \beta_{14} CFO_{it+1} + \varepsilon_i$$

	B1	***B2***	***B3***	***B4***	***B5***	***B6***	***B7***
LLP_{it-1}	-0.055	-0.127	-0.200	-0.055	-0.179	-0.199	-0.126
	(4.08)***	(8.12)***	(11.25)***	(4.21)***	(10.03)***	(11.43)***	(8.31)***
$SIZE_{it}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(2.41)**	(2.63)***	(1.88)*	(1.94)*	(2.41)**	(1.50)	(2.46)**
$EBTP_{it}$	-0.000	0.021	-0.003	-0.001	0.012	-0.004	0.020
	(0.01)	(1.05)	(0.30)	(0.08)	(0.71)	(0.34)	(0.97)
$CAPB_{it}$	-0.001	0.003	-0.006	-0.001	-0.000	-0.007	0.002
	(0.54)	(0.43)	(1.98)**	(0.73)	(0.02)	(2.11)**	(0.33)
$\Delta UNEMP_{it}$	-0.019	-0.015	-0.019	-0.019	-0.015	-0.019	-0.015
	(17.53)***	(7.67)***	(16.78)***	(17.98)***	(8.19)***	(16.86)***	(7.63)***
ΔGDP_{it}	-0.092	-0.066	-0.090	-0.093	-0.069	-0.090	-0.066
	(7.80)***	(3.11)***	(7.05)***	(8.05)***	(3.46)***	(7.04)***	(3.10)***
LLP_{it}	0.983	0.854	0.991	0.980	0.863	0.988	0.846
	(65.37)***	(55.51)***	(81.39)***	(59.90)***	(40.97)***	(74.88)***	(48.87)***
$GROWTH_{it}$	0.073	0.058	0.061	0.072	0.059	0.060	0.057
	(4.41)***	(5.39)***	(7.10)***	(4.40)***	(6.61)***	(7.34)***	(4.83)***
$LOSS_{it}$	0.000	-0.001	-0.000	0.000	-0.001	-0.000	-0.001
	(0.11)	(3.68)***	(1.65)*	(0.40)	(3.88)***	(1.49)	(3.79)***
$LOANINT_{it}$	-0.011	-0.008	-0.010	-0.011	-0.008	-0.010	-0.008
	(40.08)***	(14.24)***	(19.05)***	(40.86)***	(13.93)***	(19.94)***	(13.84)***
$INCDIV_{it}$	-0.001	-0.001	-0.002	-0.001	-0.002	-0.002	-0.001
	(3.49)***	(2.43)**	(5.44)***	(2.85)***	(3.24)***	(5.07)***	(2.09)**
CFO_{it+1}	-0.006	-0.007	-0.005	-0.006	-0.007	-0.005	-0.007
	(3.22)***	(2.50)**	(4.11)***	(3.20)***	(3.49)***	(3.76)***	(2.64)***
CFO_{it}	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	(2.26)**	(1.06)	(5.97)***	(2.29)**	(1.61)	(5.19)***	(1.12)
CFO_{it-1}	-0.000	-0.002	-0.011	-0.000	-0.007	-0.011	-0.002
	(0.00)	(0.29)	(2.79)***	(0.03)	(1.23)	(2.72)***	(0.30)
$cons$	0.005	-0.000	0.006	0.005	0.001	0.007	0.000
	(4.58)***	(0.15)	(5.11)***	(5.27)***	(0.58)	(6.14)***	(0.08)
R^2	0.96	0.79	0.92	0.96	0.79	0.92	0.78
R^2_{adj}	0.96	0.79	0.92	0.96	0.79	0.92	0.78
F	2,347.89	174.55	1,401.28	2,328.21	179.67	1,385.67	164.30
N	1,851	1,851	1,851	1,851	1,851	1,851	1,851

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using two-way clustering at the firm and year level (e.g. Petersen 2008; Gow et al. 2010). All variables are defined in Appendix 3.A.

Table 3.13
Multivariate regressions to study omitted correlated variables in basic models B1-B7

Dependent variable: absolute value of discretionary loan loss provisions ($DLLP\_abs$)

$$DLLP\_abs_{it} = \alpha + \beta_1 LLP_{it-1} + \beta_2 SIZE_{it} + \beta_3 EBTP_{it} + \beta_4 CAPB_{it} + \beta_5 \Delta UNEMP_{it} + \beta_6 \Delta GDP_{it} + \beta_7 LLP_{it} + \beta_8 GROWTH_{it} + \beta_9 LOSS_{it} + \beta_{10} LOANINT_{it} + \beta_{11} INCDIV_{it} + \beta_{12} CFO_{it-1} + \beta_{13} CFO_{it} + \beta_{14} CFO_{it+1} + \varepsilon_i$$

	B1	***B2***	***B3***	***B4***	***B5***	***B6***	***B7***
LLP_{it-1}	-0.039	-0.015	-0.056	-0.039	-0.019	-0.057	-0.016
	(2.94)***	(0.89)	(1.34)	(2.92)***	(0.83)	(1.36)	(0.95)
$SIZE_{it}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(1.24)	(2.07)**	(1.77)*	(1.22)	(2.09)**	(1.80)*	(2.19)**
$EBTP_{it}$	-0.059	-0.046	-0.059	-0.060	-0.045	-0.060	-0.049
	(2.86)***	(2.86)***	(2.55)**	(3.00)***	(2.62)***	(2.66)***	(3.22)***
$CAPB_{it}$	0.007	0.009	0.012	0.007	0.010	0.012	0.009
	(1.72)*	(2.10)**	(2.18)**	(1.79)*	(1.99)**	(2.17)**	(2.21)**
$\Delta UNEMP_{it}$	0.001	-0.002	-0.001	0.001	-0.003	-0.001	-0.002
	(0.33)	(1.21)	(0.48)	(0.31)	(2.23)**	(0.48)	(1.04)
ΔGDP_{it}	0.001	-0.026	-0.024	0.001	-0.042	-0.024	-0.024
	(0.04)	(1.83)*	(0.87)	(0.02)	(2.80)***	(0.86)	(1.41)
LLP_{it}	0.532	0.426	0.482	0.533	0.409	0.483	0.426
	(11.17)***	(15.38)***	(9.33)***	(10.99)***	(16.90)***	(9.20)***	(15.36)***
$GROWTH_{it}$	0.027	0.002	0.013	0.029	0.002	0.015	0.005
	(2.28)**	(0.27)	(1.53)	(2.35)**	(0.26)	(1.62)	(0.47)
$LOSS_{it}$	-0.001	-0.000	-0.000	-0.001	-0.000	-0.001	-0.000
	(0.94)	(0.23)	(0.57)	(0.96)	(0.13)	(0.62)	(0.40)
$LOANINT_{it}$	0.001	0.000	0.000	0.001	0.000	0.000	0.000
	(0.81)	(0.08)	(0.27)	(0.90)	(0.19)	(0.37)	(0.36)
$INCDIV_{it}$	-0.000	0.001	0.000	-0.000	0.001	0.000	0.000
	(0.29)	(0.97)	(0.65)	(0.36)	(0.89)	(0.59)	(0.71)
CFO_{it+1}	-0.003	-0.001	0.001	-0.003	0.001	0.001	-0.001
	(3.87)***	(0.74)	(1.77)*	(3.78)***	(0.95)	(1.53)	(0.70)
CFO_{it}	-0.001	-0.004	-0.003	-0.001	-0.005	-0.003	-0.004
	(0.58)	(2.56)**	(1.23)	(0.57)	(3.06)***	(1.20)	(2.33)**
CFO_{it-1}	0.006	0.008	0.010	0.006	0.010	0.010	0.008
	(2.24)**	(2.33)**	(2.89)***	(2.36)**	(2.41)**	(2.95)***	(2.56)**
$cons$	0.003	0.004	0.004	0.002	0.004	0.004	0.004
	(1.15)	(2.45)**	(1.52)	(1.12)	(2.40)**	(1.51)	(2.55)**
R^2	0.60	0.51	0.52	0.59	0.48	0.52	0.50
R^2_{adj}	0.59	0.50	0.51	0.59	0.47	0.51	0.50
F	59.11	40.65	43.91	58.88	35.97	43.98	39.64
N	1,851	1,851	1,851	1,851	1,851	1,851	1,851

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using two-way clustering at the firm and year level (e.g. Petersen 2008; Gow et al. 2010). All variables are defined in Appendix 3.A.

Table 3.14
Multivariate regressions to study omitted correlated variables in static models S1-S4 and dynamic models D1-D4

Dependent variable: signed value of discretionary loan loss provisions ($DLLP$)

$$DLLP_{it} = \alpha + \beta_1 LLP_{it-1} + \beta_2 SIZE_{it} + \beta_3 EBTP_{it} + \beta_4 CAPB_{it} + \beta_5 \Delta UNEMP_{it} + \beta_6 \Delta GDP_{it} + \beta_7 LLP_{it} + \beta_8 GROWTH_{it} + \beta_9 LOSS_{it} + \beta_{10} LOANINT_{it} + \beta_{11} INCDIV_{it} + \beta_{12} CFO_{it-1} + \beta_{13} CFO_{it} + \beta_{14} CFO_{it+1} + \varepsilon_i$$

	S1	***S2***	***S3***	***S4***	***D1***	***D2***	***D3***	***D4***
LLP_{it-1}	-0.178	-0.179	-0.182	-0.181	-0.398	-0.386	-0.389	-0.378
	(10.06)***	(10.26)***	(9.74)***	(10.22)***	(27.15)***	(28.07)***	(29.87)***	(31.81)***
$SIZE_{it}$	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(2.27)**	(2.51)**	(1.53)	(2.26)**	(1.59)	(3.17)***	(1.01)	(2.82)***
$EBTP_{it}$	0.012	0.042	-0.003	0.039	0.003	0.027	-0.008	0.025
	(0.65)	(2.34)**	(0.21)	(2.51)**	(0.27)	(2.44)**	(0.74)	(2.31)**
$CAPB_{it}$	-0.001	0.023	0.001	0.023	0.004	0.022	0.005	0.022
	(0.10)	(3.58)***	(0.12)	(3.59)***	(0.97)	(5.27)***	(1.19)	(5.09)***
$\Delta UNEMP_{it}$	-0.015	-0.016	-0.015	-0.016	-0.013	-0.015	-0.013	-0.014
	(8.09)***	(8.74)***	(7.48)***	(8.12)***	(10.22)***	(11.08)***	(9.75)***	(10.57)***
ΔGDP_{it}	-0.070	-0.082	-0.067	-0.078	-0.045	-0.056	-0.044	-0.055
	(3.41)***	(4.01)***	(2.96)***	(3.51)***	(3.07)***	(3.86)***	(2.78)***	(3.50)***
LLP_{it}	0.855	0.858	0.831	0.837	0.873	0.874	0.853	0.856
	(38.24)***	(40.68)***	(48.44)***	(50.76)***	(44.24)***	(46.90)***	(50.90)***	(53.50)***
$GROWTH_{it}$	0.058	0.062	0.059	0.061	0.017	0.022	0.020	0.024
	(5.93)***	(6.68)***	(6.65)***	(7.40)***	(1.52)	(2.14)**	(1.93)*	(2.46)**
$LOSS_{it}$	-0.001	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000	-0.001
	(4.05)***	(3.93)***	(3.52)***	(3.51)***	(2.50)**	(2.63)***	(1.96)*	(2.07)**
$LOANINT_{it}$	-0.008	-0.009	-0.008	-0.009	-0.007	-0.007	-0.006	-0.007
	(13.83)***	(15.81)***	(12.32)***	(14.45)***	(12.62)***	(14.99)***	(10.23)***	(12.29)***
$INCDIV_{it}$	-0.002	-0.002	-0.001	-0.001	-0.000	-0.000	-0.000	-0.000
	(2.93)***	(2.98)***	(3.15)***	(3.19)***	(0.91)	(1.17)	(0.24)	(0.62)
CFO_{it+1}	-0.007	-0.007	-0.006	-0.006	-0.004	-0.004	-0.003	-0.004
	(3.72)***	(3.58)***	(2.90)***	(2.93)***	(2.98)***	(2.92)***	(1.85)*	(1.98)**
CFO_{it}	0.004	0.005	0.002	0.002	0.003	0.003	0.001	0.001
	(1.71)*	(1.72)*	(0.70)	(0.83)	(1.19)	(1.26)	(0.35)	(0.50)
CFO_{it-1}	-0.007	-0.006	-0.006	-0.005	0.000	0.000	0.001	0.001
	(1.18)	(1.12)	(0.86)	(0.86)	(0.12)	(0.06)	(0.28)	(0.21)
$cons$	0.002	0.007	0.002	0.007	0.002	0.006	0.002	0.006
	(0.88)	(3.40)***	(0.96)	(3.00)***	(1.13)	(4.05)***	(1.17)	(3.59)***
R^2	0.78	0.78	0.76	0.76	0.87	0.86	0.84	0.85
R^2_{adj}	0.78	0.78	0.75	0.76	0.86	0.86	0.84	0.84
F	169.70	185.44	150.12	169.08	231.17	237.52	191.55	207.07
N	1,851	1,851	1,851	1,851	1,851	1,851	1,851	1,851

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using two-way clustering at the firm and year level (e.g. Petersen 2008; Gow et al. 2010). All variables are defined in Appendix 3.A.

Table 3.15
Multivariate regressions to study omitted correlated variables in static models S1-S4 and dynamic models D1-D4

Dependent variable: absolute value of discretionary loan loss provisions ($DLLP\_abs$)

$$DLLP\_abs_{it} = \alpha + \beta_1 LLP_{it-1} + \beta_2 SIZE_{it} + \beta_3 EBTP_{it} + \beta_4 CAPB_{it} + \beta_5 \Delta UNEMP_{it} + \beta_6 \Delta GDP_{it} + \beta_7 LLP_{it} + \beta_8 GROWTH_{it} + \beta_9 LOSS_{it} + \beta_{10} LOANINT_{it} + \beta_{11} INCDIV_{it} + \beta_{12} CFO_{it-1} + \beta_{13} CFO_{it} + \beta_{14} CFO_{it+1} + \varepsilon_i$$

	S1	***S2***	***S3***	***S4***	***D1***	***D2***	***D3***	***D4***
LLP_{it-1}	-0.020	-0.028	-0.030	-0.035	0.053	0.045	0.033	0.027
	(0.86)	(1.25)	(1.43)	(1.95)*	(1.05)	(0.96)	(0.82)	(0.70)
$SIZE_{it}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(2.30)**	(1.29)	(1.77)*	(0.84)	(2.45)**	(1.87)*	(2.23)**	(1.49)
$EBTP_{it}$	-0.048	-0.038	-0.046	-0.036	-0.054	-0.042	-0.051	-0.041
	(2.98)***	(3.05)***	(2.88)***	(2.93)***	(3.68)***	(3.20)***	(3.38)***	(3.09)***
$CAPB_{it}$	0.010	0.008	0.011	0.009	0.007	0.006	0.008	0.007
	(2.03)**	(1.13)	(1.97)**	(1.15)	(1.27)	(0.84)	(1.46)	(0.98)
$\Delta UNEMP_{it}$	-0.003	-0.003	-0.003	-0.003	-0.002	-0.003	-0.002	-0.002
	(1.99)**	(2.08)**	(1.88)*	(1.94)*	(1.53)	(1.77)*	(1.49)	(1.65)*
ΔGDP_{it}	-0.040	-0.038	-0.035	-0.033	-0.037	-0.039	-0.032	-0.032
	(2.31)**	(2.20)**	(2.21)**	(2.11)**	(1.87)*	(1.99)**	(1.79)*	(1.87)*
LLP_{it}	0.410	0.400	0.407	0.398	0.359	0.353	0.364	0.358
	(16.82)***	(16.14)***	(14.67)***	(15.21)***	(11.74)***	(12.43)***	(10.12)***	(10.68)***
$GROWTH_{it}$	0.005	-0.003	0.003	-0.003	0.014	0.007	0.009	0.004
	(0.53)	(0.30)	(0.32)	(0.30)	(2.68)***	(0.95)	(1.35)	(0.47)
$LOSS_{it}$	-0.000	-0.000	0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.29)	(0.06)	(0.03)	(0.14)	(0.42)	(0.16)	(0.04)	(0.13)
$LOANINT_{it}$	0.000	-0.000	0.001	0.000	-0.000	-0.001	0.000	-0.000
	(0.57)	(0.09)	(1.09)	(0.52)	(0.51)	(0.92)	(0.02)	(0.28)
$INCDIV_{it}$	0.000	0.000	0.001	0.000	-0.000	-0.000	0.000	0.000
	(0.71)	(0.49)	(1.01)	(0.83)	(0.26)	(0.49)	(0.15)	(0.13)
CFO_{it+1}	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.76)	(0.62)		(3.10)***	(0.85)	(0.92)	(1.11)	(1.11)
CFO_{it}	-0.005	-0.004	-0.006	-0.006	-0.005	-0.005	-0.005	-0.005
	(2.75)***	(2.20)**	(3.68)***	(3.35)***	(1.69)*	(1.93)*	(1.81)*	(2.12)**
CFO_{it-1}	0.010	0.008	0.007	0.006	0.008	0.007	0.006	0.005
	(2.52)**	(1.99)**	(1.99)**	(1.77)*	(2.02)**	(1.81)*	(1.46)	(1.41)
$cons$	0.004	0.004	0.003	0.003	0.005	0.005	0.004	0.004
	(2.48)**	(1.87)*	(1.77)*	(1.32)	(2.45)**	(2.20)**	(2.03)**	(1.70)*
R^2	0.47	0.46	0.48	0.46	0.49	0.48	0.50	0.48
R^2_{adj}	0.47	0.46	0.47	0.46	0.49	0.48	0.49	0.48
F	35.08	32.29	36.02	32.89	30.13	27.87	30.49	27.98
N	1,851	1,851	1,851	1,851	1,851	1,851	1,851	1,851

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using two-way clustering at the firm and year level (e.g. Petersen 2008; Gow et al. 2010). All variables are defined in Appendix 3.A.

Table 3.16
Multivariate regressions to study omitted correlated variables in dynamic models D1-D4 using system GMM

	Dependent variable: signed value of discretionary loan loss provisions ($DLLP$)				Dependent variable: absolute value of discretionary loan loss provisions ($DLLP\_abs$)			
LLP_{it-1}	-0.379	-0.268	-0.424	-0.290	0.064	-0.063	0.042	-0.062
	(15.58)***	(11.52)***	(19.08)***	(13.72)***	(1.31)	(2.56)**	(0.72)	(2.61)***
$SIZE_{it}$	0.000	-0.001	0.000	-0.001	-0.000	0.001	-0.000	0.000
	(1.84)*	(7.14)***	(1.92)*	(7.81)***	(2.08)**	(2.10)**	(1.44)	(2.09)**
$EBTP_{it}$	0.015	-0.057	0.020	-0.044	-0.051	-0.057	-0.059	-0.054
	(0.77)	(2.21)**	(0.91)	(1.80)*	(3.57)***	(1.67)*	(3.19)***	(1.66)*
$CAPB_{it}$	0.010	0.243	0.007	0.220	0.007	0.098	0.007	0.089
	(1.42)	(28.24)***	(1.31)	(28.04)***	(1.34)	(5.90)***	(1.02)	(5.82)***
$\Delta UNEMP_{it}$	-0.010	-0.011	-0.009	-0.011	-0.004	0.006	-0.003	0.005
	(4.51)***	(4.29)***	(3.05)***	(4.29)***	(3.64)***	(2.05)**	(1.52)	(1.79)*
ΔGDP_{it}	-0.035	-0.041	-0.019	-0.042	-0.047	0.068	-0.030	0.059
	(1.37)	(1.48)	(0.52)	(1.40)	(3.02)***	(2.01)**	(1.26)	(1.79)*
LLP_{it}	0.787	0.772	0.872	0.786	0.341	0.242	0.344	0.248
	(27.25)***	(32.02)***	(42.61)***	(38.12)***	(6.92)***	(5.45)***	(7.68)***	(5.90)***
$GROWTH_{it}$	0.014	0.079	-0.008	0.075	0.007	0.002	0.010	-0.002
	(0.66)	(4.43)***	(0.43)	(4.45)***	(0.72)	(0.10)	(0.91)	(0.13)
$LOSS_{it}$	-0.001	-0.001	-0.001	-0.001	0.000	0.002	-0.000	0.001
	(2.32)**	(2.72)***	(1.85)*	(2.56)**	(0.65)	(1.88)*	(0.57)	(1.78)*
$LOANINT_{it}$	-0.006	-0.014	-0.016	-0.015	-0.000	-0.006	-0.001	-0.005
	(6.67)***	(15.47)***	(19.60)***	(18.59)***	(0.04)	(3.85)***	(1.07)	(3.86)***
$INCDIV_{it}$	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001
	(0.05)	(1.71)*	(0.34)	(1.63)	(0.87)	(0.98)	(0.97)	(1.04)
CFO_{it+1}	-0.005	-0.011	-0.008	-0.011	0.001	-0.005	-0.002	-0.005
	(1.73)*	(2.22)**	(3.08)***	(2.37)**	(0.54)	(1.73)*	(0.78)	(1.91)*
CFO_{it}	0.002	0.006	0.007	0.006	-0.005	-0.002	-0.005	-0.002
	(0.54)	(0.92)	(1.46)	(0.98)	(2.15)**	(0.89)	(1.83)*	(0.91)
CFO_{it-1}	0.006	0.005	0.003	0.005	0.008	0.000	0.008	0.001
	(1.06)	(0.59)	(0.46)	(0.59)	(2.24)**	(0.02)	(4.08)***	(0.11)
$cons$	-0.002	0.006	0.005	0.010	0.005	-0.010	0.006	-0.009
	(0.55)	(1.69)*	(1.84)*	(2.71)***	(2.55)**	(1.90)*	(3.07)***	(1.81)*
R^2	0.62	0.80	0.67	0.80	0.42	0.26	0.35	0.26
R^2_{adj}	0.62	0.80	0.67	0.80	0.41	0.26	0.34	0.26
F	62.72	433.92	116.64	417.30	22.57	18.49	19.26	18.83
N	1,851	1,851	1,851	1,851	1,851	1,851	1,851	1,851

$$DLLP_{it}\ (DLLP\_abs_{it}) = \alpha + \beta_1 LLP_{it-1} + \beta_2 SIZE_{it} + \beta_3 EBTP_{it} + \beta_4 CAPB_{it} + \beta_5 \Delta UNEMP_{it} + \beta_6 \Delta GDP_{it} + \beta_7 LLP_{it} + \beta_8 GROWTH_{it} + \beta_9 LOSS_{it} + \beta_{10} LOANINT_{it} + \beta_{11} INCDIV_{it} + \beta_{12} CFO_{it-1} + \beta_{13} CFO_{it} + \beta_{14} CFO_{it+1} + \varepsilon_i$$

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using two-way clustering at the firm and year level (e.g. Petersen 2008; Gow et al. 2010). All variables are defined in Appendix 3.A.

Tables 3.13, 3.15 and 3.16 show the results for absolute discretionary LLP on omitted variables. For the set of further controls, we find significant coefficients when these have not been added to the first stage of the regressions. Since $EBTP_{it}$ and $CAPB_{it}$, are likely to capture EM incentives of capital management and earnings smoothing, we cannot distinguish between signs of high or low quality of the respective model. For models ***S2***, ***S4***, ***D2*** & ***D4*** where we include the further set of controls, significances and therefore influences of size and capital adequacy on the inferences drawn from the model are no longer existent.[56] This could also entail disproportionate exclusion of discretionary variation from the total LLP, which

[56] However, when regressions use system GMM in the first stage (table 3.16), influences of size, performance and capital adequacy are still pronounced, especially when they are included in the first place. Still left with two possible explanations, these results indicate less proper exclusion of variation caused by these variables on the first stage compared to the remaining models.

would decrease the quality of the model. What is more, we still find significant regressors for $EBTP_{it}$.[57] Altogether, adding a further set of controls should follow careful considerations of which inferences are to be drawn and possible non-linearity of the variables.

When we compare the results for the coefficients on the variables $GROWTH_{it}$, $LOANINT_{it}$, $INCDIV_{it}$ and the CFO variables in table 3.12, 3.14 & 3.16, we find significant influences on the variation of non-absolute discretionary LLP. In contrast, we do not find consistent results for the absolute value of discretionary LLP except for CFO_{it} and CFO_{it-1}. Even though all of these omitted and possibly correlated variables do not seem to significantly influence the variation of $DLLP\_abs_{it}$, they seem to explain variation of discretionary LLP to a certain degree, as indicated by the significances for the regressions using signed values. Therefore, including these variables in the first-stage of the EM modelling process could help explain considerable variation of total LLP. If this variation turns out to be mostly non-discretionary, inferences drawn from the second stage could be consolidated. In particular, mapping the relationship between cash-flows and non-discretionary variation of total LLP by including all three (e.g. McNichols, 2002) or certain fractions of CFO into a model could improve the quality of our discretionary LLP proxy.

3.4.5 Test for prediction power

Tables 3.17 to 3.19 include the results of the prediction power test procedure.[58] To analyse the results, we differentiate between two odds. The first value ($Correct\ if\ CRKQ = 1$) indicates the percentage of observations, in which our regression results, given that probable EM had been criticized by the SEC or restated by the firm, correctly predicts EM (Odds > 0.5; positive prediction). The second value shows the respective percentage of observations, in which no EM is predicted (Odds < 0.5; negative prediction), given that the SEC or firm had issued no comment or restatement letters on EM related topics. Therefore, a higher value in both percentages indicates a better prediction power.

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[57] We are still left with two alternative explanations, hence the lacking isolation of non-discretionary and discretionary LLP and the recognition of EM through the model

[58] We have to exclude all banks without an entry at the SEC, which reduces our sample to 1,826 firm-year observations.

Table 3.17 shows the results for basic models. Model ***B1*** accomplishes to positively predict 20.27% cases of potential EM. Adding more explanatory variables into the regression substantially increases the positive prediction power. The only exception is model ***B4***, which is not surprising, as the sole inclusion of NCO_{it} already has no improving effect on the first stage, as indicated by the differences in adjusted R^2 and BIC we discussed earlier. The highest increase in positive prediction power is achieved by including the non-performing assets pattern (NPA_{it-1} and ΔNPA_{it}), either solely (27.99%) or in combination with ALW_{it-1} (28.73%). However, the combination of NPA and NCO patterns results in the highest positive prediction value (28.98%). Regarding negative predictions, the results only vary by a small margin (86.20% to 85.03%). Overall, ***B7*** seems to produce the best trade-off between positive and negative predictions.

The results for static and dynamic models vary by a large margin. The highest positive prediction values are achieved in models ***S1*** and ***S3*** (29.73%). The addition of controls for size, performance and capital requirement decreases the positive prediction power by a large portion (26.99% in ***S2*** and 28.98% in ***S4***), which might underline that these controls (particularly performance and capital adequacy) capture actual EM incentives to some degree. Given the assumption of actual use of EM in every year, an inclusion of these variables results in the removal of discretionary variation from total LLP in the first stage, which leaves the resulting proxy with a lower probability of verifying EM when it actually occurs.

What is more, the introduction of a dynamic modelling already seems to introduce additional bias. Model ***D1*** achieves the lowest positive prediction power, with only 24.00%, which is even lower than most of the basic models. Likewise all other dynamic models produce less appropriate proxies for means of predicting EM. We present two explanations for this result. First, the introduction of an additional lagged dependent variable as a regressor does not add any value to modelling non-discretionary variation in total LLP, but actually colludes with discretionary LLP in the current year. Second, simple assumption of no endogeneity in the models estimated using pooled OLS with two-way clustering tends to lead to biased coefficients for this variable and therefore biases the resulting discretionary proxies. To cancel out the second reason, we alternatively apply the dynamic models with a system GMM estimator. Here, results vary widely. For model ***D1***, the positive prediction value increases from 24.00% to 27.39%, while it is still considerably lower than the prediction value for model ***S1*** (29.73%). For all other models, values decrease substantially, i.e. for model ***D2*** the positive prediction value more than halves from 25.25% to 12.31%.[59] These results could indicate that that our first explanation for the decrease in positive prediction power for dynamic modelling approaches is valid. However, we cannot cancel out that estimation efficiency of system GMM estimators is lacking in our small sample size or the remaining regressors in the first-stage regressions should also be assumed to be endogenous to produce appropriate results (e.g. Bouvatier et al., 2014).[60]

Table 3.17
Prediction tests for basic models B1-B7

Dependent variable: Comment/restatement of K-10/Q-10 report ($CRKQ$)

$$CRKQ_{it} = \alpha + \beta ARES_{it} + \varepsilon_i$$

	B1	***B2***	***B3***	***B4***	***B5***	***B6***	***B7***
$ARES_{it}$	125.730	169.846	145.988	124.027	178.302	145.002	169.782
	(6.72)***	(8.23)***	(7.46)***	(6.65)***	(8.39)***	(7.42)***	(8.17)***
$cons$	-0.727	-0.806	-0.778	-0.719	-0.828	-0.773	-0.803
	(8.43)***	(9.69)***	(9.06)***	(8.37)***	(9.84)***	(9.02)***	(9.65)***
$Correct\ if\ CRKQ = 1$	20.27%	27.99%	25.50%	20.27%	28.73%	25.50%	28.98%
$Correct\ if\ CRKQ = 0$	86.01%	85.03%	86.20%	86.01%	85.32%	85.71%	85.52%
R_p^2	0.02	0.03	0.02	0.02	0.03	0.02	0.03
chi^2	50.02	75.67	62.06	48.89	79.67	61.33	74.59
N	1,826	1,826	1,826	1,826	1,826	1,826	1,826

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using logistic regressions. All variables are defined in Appendix 3.A.

[59] This result is in line with the problem of including the set of further controls discussed earlier. Regarding the negative prediction power, models ***D1*** and ***D4*** result in the best negative prediction values (88.65% and 87.77%), which is likely to be caused by the decrease in positive prediction power, hence no sign of efficient modelling.

[60] As discussed earlier, such an assumption would question most of the applied specifications in bank accounting research, which assume all regressors to be exogenous.

Table 3.18
Prediction tests for static models S1-S4 and dynamic models D1-D4

Dependent variable: Comment/restatement of K-10/Q-10 report ($CRKQ$)

$$CRKQ_{it} = \alpha + \beta ARES_{it} + \varepsilon_i$$

	S1	*S2*	*S3*	*S4*	*D1*	*D2*	*D3*	*D4*
$ARES_{it}$	178.313	166.507	177.870	165.114	155.642	154.683	158.496	155.785
	(8.34)***	(7.53)***	(8.18)***	(7.34)***	(7.14)***	(6.84)***	(7.19)***	(6.85)***
$cons$	-0.826	-0.785	-0.806	-0.765	-0.685	-0.683	-0.682	-0.676
	(9.80)***	(9.11)***	(9.66)***	(8.95)***	(8.81)***	(8.58)***	(8.84)***	(8.57)***
$Correct\ if\ CRKQ = 1$	29.73%	26.99%	29.73%	28.98%	24.00%	25.25%	25.00%	25.25%
$Correct\ if\ CRKQ = 0$	84.93%	86.20%	85.71%	86.69%	86.89%	87.28%	86.50%	87.77%
R_p^2	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02
chi^2	78.73	63.13	75.69	60.02	57.58	52.87	58.41	52.92
N	1,826	1,826	1,826	1,826	1,826	1,826	1,826	1,826

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using logistic regressions. All variables are defined in Appendix 3.A.

Table 3.19
Prediction tests for dynamic models D1-D4 using system GMM

Dependent variable: Comment/restatement of K-10/Q-10 report ($CRKQ$)

$$CRKQ_{it} = \alpha + \beta ARES_{it} + \varepsilon_i$$

	D1	*D2*	*D3*	*D4*
$ARES_{it}$	153.200	62.480	140.209	68.627
	(7.49)***	(5.37)***	(7.35)***	(5.50)***
$cons$	-0.703	-0.607	-0.776	-0.624
	(9.09)***	(7.33)***	(8.97)***	(7.42)***
$Correct\ if\ CRKQ = 1$	27.49%	12.31%	23.64%	14.05%
$Correct\ if\ CRKQ = 0$	85.13%	88.65%	86.99%	87.77%
R_p^2	0.03	0.01	0.02	0.01
chi^2	63.78	31.68	60.16	33.13
N	1,826	1,826	1,826	1,826

*, **, *** Indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, based on two-tailed tests. All test statistics are calculated using logistic regressions. All variables are defined in Appendix 3.A

3.5 Conclusion

This study tries to analyse modelling of EM in the banking sector. In particular, we analyse the prior literature and identify common specification patterns, examine them and thereby set up various models that capture commonly used specification pattern parts. Consequently, we apply various established statistical methods to test the validity of the models concerning measurement errors, omitted variable biases and prediction power. What is more, we investigate basic models for settings with data limitations, which are characterised by the absence of potential important specification pattern groups. Applying these models, we additionally try to gain insights about the influence on explanatory and predictive power

Our results show that the pattern group of non-performing assets is by far the most important influencing factor of non-discretionary variation and therefore a potentially non-disputable data insufficiency variable. The pattern group loan loss allowances can enhance modelling if solely used but looses most of its explanatory and predictive power when used in combination with the NPA patterns. NCO patterns seem to be dispensable, as they exert only limited influence on non-discretionary variation in first stage regressions and only if used together with NPA patterns. Dynamic models could be superior to static models and should be applied, as there is no loss in observations, if NPA patterns are already used in first stage regression. However, the efficient application of dynamic modelling has to be examined, e.g., choice of estimators. Regarding measurement errors and extreme performance bias, our results indicate that commonly used EM proxies do not suffer from measurement errors but are correlated with extreme CFO performance. Tests for omitted and possibly correlated variables uncover some interesting insights regarding size, performance and capital requirements. All these variables seem to influence loan loss provisioning in a non-linear way and should therefore be implemented as such. Moreover, our results indicate that the inclusion of certain variables, e.g., variables for growth, income diversification, loan intensity and cash flows may potentially improve the quality of EM proxies.

The results for the prediction power test are somewhat different from first stage results. For our data limitation models, we see an increase in positive prediction power in accordance to the results of the first stage regressions: NPA is a main driver of positive predictive power. Regarding the full-specified static and dynamic models, we see that introduction of $SIZE_{it}$, $EBTP_{it}$ and $CAPB_{it}$ reduces the positive prediction power, while additional lags and forwards of NPA have no effect. Regarding static and dynamic models, the result differs compared to first stage regression. Positive prediction power decreases by a large margin. Hence, in research environments, in which the prediction power of EM proxies is relevant, static models are superior.

This study also has some possible limitations. The proposed and tested models as well as the strand of literature focusing on residual proxies could suffer from insufficient separation of non-discretionary and discretionary accrual parts on the first stage, making two-step approaches a biased way of modelling. In particular, when on the second stage correlated non-discretionary variables explaining variation in the discretionary proxy that actually includes non-discretionary variation are not included. However, none of our analyses could be applied in a one-step approach and we try to ex-post check for the validity of the models in this regard. Furthermore, we focus only on one accrual, which cancels out noisy variation in the total accrual amount caused by any other accrual we are not able to map with our non-discretionary regressors. However, we propose future research papers to check for robustness of their results using both one- and two-step approaches, while using residuals from the first-stage for descriptive reasons. Future research should also focus on integrating our omitted and possibly correlated variables to further check for the robustness of their results and possibly improve their modelling of discretionary LLP. This could help to improve the specifications and therefore the modelling process of EM going forward.

Appendix 3.A – Variable definitions

Variable	Definition
	Variables applied in basic models B1-B7
LLP	Total loan loss provisions.
NPA	Non-performing loans/assets.
ΔNPA	Change in non-performing assets.
ALW	Loan loss allowances/reserves.
TL	Total loans.
ΔTL	Change in total loans.
$TL\_CATEGORIES$	Total loan categories, calculated as fraction of loans associated to the respective loan category for each of the categories analysed.
NCO	Net charge-offs, calculated as loan losses minus recoveries.
	Additional variables applied in static and dynamic models S1-S4 and D1-D4
$SIZE$	Bank size, calculated as the natural logarithm of total assets.
$EBTP$	Earnings before tax and provisions, scaled by lagged total assets.
$CAPB$	Capital adequacy ratio, calculated as tier 1 capital, scaled by lagged total assets.
	Control variables
ΔGDP	Change in GDP for country j the respective bank i is located, from year t-1 to year t.
$\Delta UNEMP$	Change in unemployment rate for country j the respective bank i is located, from year t-1 to year t.
$\Delta LandPrice$	Change in land prices, e.g., calculated as change in a land price index.
$CSRET$	Return on the Case-Shiller Real estate Index.
ΔBFI	Change in a business failure index.
ΔSDA	Change in implied standard deviation of bank asset values.
	Proxies for earnings management
$DLLP$ ($DLLP\_abs$)	Discretionary loan loss provisions, comprehended as the signed (absolute) value of the residual from first-stage regressions.
	Proxy for extreme performance
CFO	Cash-flow from operations.
	Variables for OMV-test
$GROWTH$	Change in sales, scaled by lagged total assets.
$LOSS$	Dummy variable, which equals 1 if net income before extraordinary items is negative, 0 otherwise.
$LOANINT$	Loan intensity, calculated as total loans scaled by total assets.
$INCDIV$	Income diversification, calculated as non-interest income scaled by interest income.

Proxy for earnings management detection	
$ARES$	Average residual, calculated as mean value of DLLP for each bank.
$CRKQ$	Comment/restatement of K-10/Q-10 report. Dummy variable, which equals 1 if the respective bank received a SEC comment letter on their annual (K-10) or quarterly (Q-10) financial report with respect to the treatment of loan loss provisioning and related issues; or the respective bank restated its K-10 or Q-10 report because of insufficiencies regarding the treatment of loan provisioning and related issues.

Appendix 3.B – List of specifications

No.	***Authors***	***Sample***	***Sample period***	***One vs. two-step models***	***Specification***
Papers used in Beatty and Liao (2014)					
1	**Beatty et al. (1995)** *Journal of Accounting Research*	USA	1985-1989	One	$LLP_{it} = \alpha_0 + \beta_1 NPA_{it} + \beta_2 ALW_{it} + \varepsilon_{it}$
2	**Beaver and Engel (1996)** *Journal of Accounting and Economics*	USA	1977-1991	Two	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 NPA_{it} + \beta_3 \Delta NPA_{it+1} + \beta_4 NCO_{it} + \varepsilon_{it}$
3	**Beck and Narayanamoorthy (2013)** *Journal of Accounting and Economics*	USA	1992-2008	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it} + \beta_{2-3} TL\_CATEGORIES_{it} + \beta_4 NCO_{it} + \beta_5 ALW_{it-1} + \beta_6 SIZE_{it} + \beta_7 CSRET_{it} + \beta_8 \Delta UNEMP_{it} + \varepsilon_{it}$
4	**Bushman and Williams (2012)** *Journal of Accounting and Economics*	International	1995-2006	One	$LLP_{it} = \alpha_0 + \beta_1 NPA_{it-2} + \beta_2 NPA_{it-1} + \beta_3 \Delta NPA_{it} + \beta_4 \Delta NPA_{it+1} + \beta_5 CAPB_{it} + \beta_6 EBTP_{it} + \beta_7 SIZE_{it} + \beta_8 \Delta GDP_{it} + \varepsilon_{it}$
5	**Collins et al. (1995)** *Journal of Accounting Research*	USA	1971-1991	One	$LLP_{it} = \alpha_0 + \beta_1 NPA_{it-1} + \beta_2 \Delta NPA_{it} + \beta_3 ALW_{it-1} + \beta_4 CAPB_{it} + \beta_5 EBTP_{it} + \varepsilon_{it}$
6	**Kanagaretnam et al. (2010a)** *The Accounting Review*	International	2000-2006	Two	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 \Delta TL_{it} + \beta_{3-4} TL\_CATEGORIES_{it} + \beta_5 NPA_{it-1} + \beta_6 \Delta NPA_{it} + \beta_7 NCO_{it} + \beta_8 ALW_{it-1} + \varepsilon_{it}$
7	**Kim and Kross (1998)** *Journal of Accounting and Economics*	USA	1984-1992	One	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 \Delta TL_{it} + \beta_3 NPA_{it-1} + \beta_4 \Delta NPA_{it} + \beta_5 NCO_{it} + \beta_6 \Delta ROA_{it} + \beta_7 SIZE_{it} + \varepsilon_{it}$

8	**Liu and Ryan (2006)** *The Accounting Review*	USA	1991-2000	One	$LLP_{it} = \alpha_0 + \beta_1 TL\_CATEGORIES_{it} + \beta_2 \Delta NPA_{it} + \beta_3 CAPB_{it} + \beta_4 EBTP_{it} + \beta_5 Dum(AbMedROA)_{it} + \varepsilon_{it}$
9	**Wahlen (1994)** *The Accounting Review*	USA	1977-1988	Two	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 NPA_{it-1} + \beta_3 \Delta NPA_{it} + \beta_4 ALW_{it-1} + \varepsilon_{it}$
Other important papers					
10	**Ahmed et al. (1999)** *Journal of Accounting and Economics*	USA	1986-1995	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta NPA_{it} + \beta_2 CAPB_{it} + \beta_3 EBTP_{it} + \beta_4 \Delta BFI_{it} + \beta_5 \Delta SDA_{it} + \varepsilon_{it}$
11	**Agarwal et al. (2007)** *International Review of Economics and Finance*	Japan	1985-1999	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it} + \beta_2 ALW_{it-1} + \beta_3 DUM(Bel25QCAP)_{it-1} + \beta_4 DUM(Ab25QBel75QCAP)_{it-1} + \beta_5 DUM(Ab75QCAP)_{it-1} + \beta_6 EBTP_{it} + \beta_7 (EBTP * NEG)_{it} + \beta_8 SIZE_{it-1} + \beta_9 GAINS_{it} + \beta_{10} NETDIV_{it} + \beta_{11} \Delta LandPrice_{it} + \varepsilon_{it}$
12	**Anandarajan et al. (2007)** *Journal of Accounting, Auditing & Finance*	Australia	1991-2001	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta NCO_{it} + \beta_2 CAPB_{it} + \beta_3 EBTP_{it} + \beta_4 SIZE_{it} + \beta_5 NII_{it} + \beta_6 \Delta GDP_{it} + \varepsilon_{it}$
13	**Beatty et al. (2002)** *The Accounting Review*	USA	1988-1998	Two	$LLP_{it} = \alpha_0 + \beta_{1-6} TL\_CATEGOTIES_{it} + \beta_7 \Delta NPA_{it} + \beta_8 ALW_{it} + \beta_9 SIZE_{it} + \varepsilon_{it}$
14	**Beatty and Liao (2011)** *Journal of Accounting and Economics*	US	1993-2009	Two	$LLP_{it} = \alpha_0 + \beta_1 NPA_{it-2} + \beta_2 NPA_{it-1} + \beta_3 \Delta NPA_{it} + \beta_4 \Delta NPA_{it+1} + \beta_5 CAPB_{it} + \beta_6 EBTP_{it} + \varepsilon_{it}$
15	**Bikker and Metzemakers (2005)**	International	1991-2001	One	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 \Delta TL_{it} + \beta_3 CAPB_{it} + \beta_4 EBTP_{it} + \beta_5 \Delta GDP_{it} + \beta_6 UNEMP_{it} + \varepsilon_{it}$

	Journal of International Financial Markets, Institutions and Money				
16	**Bouvatier et al. (2014)** *Journal of Banking & Finance*	Europe	2004-2009	One	$LLP_{it} = \alpha_0 + \beta_1 LLP_{it-1} + \beta_4 TL_{it} + \beta_5 \Delta TL_{it} + \beta_3 ALW_{it-1} + \beta_4 CAPB_{it-1} + \beta_5 EBTP_{it} + \beta_6 NII_{it} + \beta_7 \Delta GDP_{jt} + \varepsilon_{it}$
17	**Bushman and Williams (2015)** *Journal of Accounting Research*	USA	1996-2009	Two	$LLP_{it} = \alpha_0 + \beta_1 \Delta NPA_{it-2} + \beta_2 \Delta NPA_{it-1} + \beta_3 \Delta NPA_{it} + \beta_4 \Delta NPA_{it+1} + \beta_5 NCO_{it} + \beta_6 CAPB_{it-1} + \beta_7 EBTP_{it} + \beta_8 SIZE_{it} + \varepsilon_{it}$
18	**Cheng et al. (2011)** *Journal of Accounting, Auditing & Finance*	USA	1994-2007	Two	$LLP_{it} = \alpha_0 + \beta_1 \frac{1}{BVE + ALW}_{it} + \beta_2 \Delta TL_{it} + \beta_3 \Delta NPA_{it} + \beta_4 \Delta NPA_{it+1} + \beta_5 NCO_{it} + \varepsilon_{it}$
19	**Cohen et al. (2014)** *Journal of Money, Credit and Banking*	USA	1997-2009	Two	$LLP_{it} = \alpha_0 + \beta_{1-5} TL\_CATEGORIES_{it} + \beta_6 NPA_{it} + \beta_7 ALW_{it} + \beta_8 SIZE_{it} + \varepsilon_{it}$
20	**DeBoskey and Jiang (2012)** *Journal of Banking & Finance*	USA	2002-2006	Two	$LLP_{it} = \alpha_0 + \beta_{1-3} TL\_CATEGORIES_{it} + \beta_4 NPA_{it} + \beta_5 \Delta NPA_{it} + \beta_6 ALW_{it} + \beta_{7-8} CAPB_{it} + \beta_9 EBTP_{it} + \beta_{10} SIZE_{it} + \beta_{11} \Delta Assets_{it} + \varepsilon_{it}$
21	**El Sood (2012)** *International Review of Financial Analysis*	USA	2001-2009	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it+1} + \beta_2 \Delta NPA_{it+1} + \beta_3 CAPB_{it} + \beta_4 SIZE_{it} + \beta_5 \Delta STDEQ_{it+1} + \varepsilon_{it}$

22	**Fonseca and Gonzalez (2008)** *Journal of Banking & Finance*	International	1995-2002	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it} + \beta_2 LLP_{it-2} + \beta_3 LLP_{it-1} + \beta_4 ALW_{it} + \beta_5 CAPB_{it} + \beta_6 EBTP_{it} + \beta_7 \Delta GDP_{it} + \varepsilon_{it}$
23	**Gebhardt and Novotny-Farkas (2011)** *Journal of Business Finance & Accounting*	International	2000-2007	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it} + \beta_2 NPA_{it-1} + \beta_3 \Delta NPA_{it} + \beta_4 CAPB_{it-1} + \beta_5 EBTP_{it} + \varepsilon_{it}$
24	**Hamadi et al. (2016)** *Journal of Banking & Finance*	International	2006-2011	Two	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 \Delta TL_{it} + \beta_3 NPA_{it} + \beta_4 \Delta NPA_{it} + \beta_5 NCO_{it} + \beta_6 CAPB_{it} + \beta_7 SIZE_{it} + \beta_8 \Delta GDP_{it} + \beta_9 \Delta UNEMP_{it} + \beta_{10} HPI_{it} + \beta_{11} TermSpread_{it} + \varepsilon_{it}$
25	**Hasan and Wall (2004)** *The Financial Review*	USA, International, Japan, Canada	1993-2000	One	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 NPA_{it} + \beta_3 NCO_{it} + \beta_4 CAPB_{it-1} + \beta_5 EBTP_{it} + Year + \varepsilon_{it}$
26	**Kanagaretnam et al. (2003)** *Review of Quantitative Finance and Accounting*	USA	1987-2000	Two	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it} + \beta_2 NPA_{it-1} + \beta_3 \Delta NPA_{it} + \varepsilon_{it}$
27	**Kanagaretnam et al. (2004)** *Contemporary Accounting Research*	USA	1980-1997	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it} + \beta_2 NPA_{it-1} + \beta_3 \Delta NPA_{it} + \beta_4 NCO_{it} + \beta_5 ALW_{it-1} + \beta_6 EBTP_{it} + \varepsilon_{it}$
28	**Kanagaretnam et al. (2005)** *Journal of Business Research*	USA	1980-1997	Two	$LLP_{it} = \alpha_0 + \beta_1 \Delta NPA_{it} + \beta_2 NCO_{it} + \beta_3 ALW_{it-1} + \beta_4 CAPB_{it} + \beta_5 EBTP_{it} + \beta_6 \Delta EBTP_{it+1} + \varepsilon_{it}$
29	**Kanagaretnam et al. (2009)** *Journal of Banking & Finance*	USA	1993-2004	Two	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it} + \beta_2 NPA_{it-1} + \beta_3 \Delta NPA_{it} + \beta_4 NCO_{it} + \beta_5 ALW_{it-1} + \beta_6 CAPB_{it} + \beta_7 EBTP_{it} + Year + \varepsilon_{it}$

30	**Kanagaretnam et al. (2010b)** *Journal of Banking & Finance*	International	1993-2006	Two	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 \Delta TL_{it} + \beta_3 TL\_CATEGORIES_{it} + \beta_4 NPA_{it} + \beta_5 \Delta NPA_{it} + \beta_6 NCO_{it} + \beta_7 ALW_{it-1} + \varepsilon_{it}$
31	**Kanagaretnam et al. (2014)** *Journal of Banking & Finance*	International	1993-2006	Two	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 \Delta TL_{it} + \beta_3 TL\_CATEGORIES_{it} + \beta_4 NPA_{it} + \beta_5 NCO_{it} + \beta_6 ALW_{it-1} + Year + Country + \varepsilon_{it}$
32	**Kanagaretnam et al. (2015)** *Journal of Business Ethics*	International	1995-2006	Two	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 \Delta TL_{it} + \beta_3 TL\_CATEGORIES_{it} + \beta_4 NPA_{it-1} + \beta_5 \Delta NPA_{it-1} + \beta_6 NCO_{it} + Year + Country + \varepsilon_{it}$
33	**Kilic et al. (2013)** *The Accounting Review*	USA	1998-2003	One	$LLP_{it} = \alpha_0 + \beta_1 TL_{it-1} + \beta_2 \Delta TL_{it} + \beta_3 NPA_{it-1} + \beta_4 \Delta NPA_{it} + \beta_5 NCO_{it} + \beta_6 ALW_{it} + \beta_7 CAPB_{it} + \beta_8 \Delta EBTP_{it} + \beta_9 Dum(Ab75QBel25QEBTP)_{it} + \varepsilon_{it}$
34	**Laeven and Majnoni (2003)** *Journal of Financial Intermediation*	International	1988-1999	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it} + \beta_2 EBTP_{it} + \beta_3 \Delta GDP_{it} + \varepsilon_{it}$
35	**Leventis et al. (2011)** *Journal of Financial Services Research*	Europe	1999-2008	One	$LLP_{it} = \alpha_0 + \beta_1 CAPB_{it} + \beta_2 EBTP_{it} + \beta_3 SIZE_{it} + \beta_4 NII_{it} + \beta_5 \Delta GDP_{it} + \varepsilon_{it}$
36	**Liu and Ryan (1995)** *Journal of Accounting Research*	USA	1983-1991	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta NPA_{it-3} + \beta_2 \Delta NPA_{it-2} + \beta_3 \Delta NPA_{it-1} + \beta_4 \Delta NPA_{it} + \varepsilon_{it}$
37	**Lobo and Yang (2001)** *Review of Quantitative Finance and Accounting*	USA	1981-1996	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it} + \beta_2 NPA_{it-1} + \beta_3 \Delta NPA_{it} + \beta_4 NCO_{it} + \beta_5 ALW_{it-1} + \beta_6 CAPB_{it} + \beta_7 EBTP_{it} + \varepsilon_{it}$
38	**Pérez et al. (2008)** *European Accounting Review*	Spain	1986-2000	One	$LLP_{it} = \alpha_0 + \beta_1 TL_{it} + \beta_2 NPA_{it} + \beta_3 CAPB_{it-1} + \beta_4 EBTP_{it} + \beta_5 SIZE_{it} + \beta_6 \Delta GDP_{t} + \beta_7 IBOL_{t} + \varepsilon_{it}$

39	**Shrieves and Dahl (2003)** *Journal of Banking & Finance*	Japan	1989-1996	One	$LLP_{it} = \alpha_0 + \beta_1 \Delta TL_{it} + \beta_2 ALW_{it-1} + \beta_3 DUM(Bel25QCAP)_{it-1} + \beta_4 DUM(Ab25QBel75QCAP)_{it-1} + \beta_5 DUM(Ab75QCAP)_{it-1} + \beta_6 EBTP_{it} + \beta_7 (EBTP * NEG)_{it} + \beta_8 SIZE_{it-1} + \beta_9 Liabilities_{it} + \beta_{10} GAINS_{it} + \beta_{11} NETDIV_{it} + \beta_{12} \Delta LandPrice_{it} + \varepsilon_{it}$

4 Board Regulation and its Impact on Composition and Effects – Evidence from German Cooperative Bank[61]

4.1 Introduction

In recent years German players of global renown revealed a rather bisected picture regarding the competence-level of supervisory boards. While some companies employ best practice corporate governance, others like Volkswagen raised the question of the state of governance mechanisms in big companies, as they failed to fulfil their function regarding monitoring and counselling. This function is very important in vital industries such as automotive and technology but even more so in the banking sector with its extraordinary importance for the overall economic state of countries. Thus, it is not surprising that research concerning board structure influences on firm performance and other important key figures is on its rise.

Beside researchers another group is increasingly interested in board composition: regulators. With the implementation of the German Act to Strengthen Financial Market and Insurance Supervision (FinVAG) the Federal Financial Supervisory Authority (BaFin) was empowered to inspect supervisory boards and individual members for their level of competence and reliability. In case of a negative verdict BaFin is empowered to initiate a removal from office. This potential consequence should unfold an incentivizing effect which will be focused on in the following study.

The present study contributes to current literature in several ways: First, the study examines a special type of banking, namely the cooperative banking, which is in current literature often overlooked despite its importance in private and corporate banking in almost every developed country. Furthermore, cooperative banks exhibit a highly different risk profile than other bank types as they are focused on the support of the local customers. Second, the study investigates coherences which are widely ignored in current literature: the occupational background of supervisory board members and its impact on risk measures. In contemporary literature various

[61] This chapter is based on a working paper titled "Board Regulation and its Impact on Composition and Effects – Evidence from German Cooperative Bank" (Stralla, 2017).

characteristics are investigated concerning diversification of the board, e.g. gender, age or educational level. Due to the unique dataset the study is able to investigate the influence of various professional groups and occupational diversification. Finally, this study is in contrast to known research, the only one investigating the influence of FinVAG, although having severe implications for central risk-measures and the board structure.

The paper proceeds as follows: Section 4.2 states the positioning of cooperative banks in the German banking sector and provides information about the purpose and execution of FinVAG. Section 4.3 reviews current corporate governance literature and describes the development of the research hypotheses. The research data and method, the GMM-estimation technique to be specific, are described in section 4.4. Section 4.5 provides information about the variables employed and descriptive statistics. Results were discussed in section 4.6. The paper concludes by a summary of most important findings.

4.2 German cooperative banks and the German Act to Strengthen Financial Market and Insurance Supervision

4.2.1 Cooperative Banks in the German Banking System

Regarding the German banking sector, the cooperative banks are one of three bank-groups, with the other two being commercial banks and savings banks. Therefore, the German banking sector is often referred to as a three-pillar-model. Cooperative banks are retail oriented which differ to some extend from commercial bank especially concerning the source of non-interest income. Thus, cooperative banks rather generate their non-interest income from commission activities than from investment banking[62]. Additionally, cooperative banks can be allotted to the group of small banks, comparable to credit unions, community banks and savings banks, which play a vital role in many developed countries (Hesse and Čihák, 2007). Most of these banks mentioned prior share the characteristic of not focusing on value-maximization but rather on supporting the members and the regional economy (e.g.

[62] Cooperative banks do not directly engage in investment banking. However, this field of operation is not completely absent, but is carried out by the cooperative banking central institute, the DZ Bank.

§1 GenG). These characteristics result in a very special risk profile. As cooperative banks are obligated to act in their predetermined region exclusively they lack the possibility of supra-regional diversification, hence having a higher risk exposure to cluster risk and dependence on the overall performance of few small and medium-sized enterprises. On the other side cooperative banks are not focused on value maximization, therefore cooperative banks are less susceptible to moral hazard behavior like pursue of short-term at the cost of future stability (Reeg and Stralla, 2016). This positive aspect may outclass the negative influence of the missing diversification possibility.

Another aspect with influence on the risk-tanking of cooperative banks is the actual lack of shareholders in a classical sense. Many studies (e.g. Galai and Masulis, 1976; Jensen and Meckling, 1976; Merton, 1977) argue that shareholders prefer more risk in comparison to bank managers as shareholders can diversify their portfolio. Therefore, shareholders tend to pressure the management to augment the returns by increasing risk. Supervisors representing the interests of shareholder demand a management behavior according to these claims. In cooperative banking members (the shareholders of cooperative banks) are not profit-driven as their equity-investment is mandatory to become a client of the bank. Furthermore, it is not possible to increase the equity investment infinitely, thus limiting the investment capability. Consequently, the risk-increasing pressure of shareholder interest should not occur in cooperative banking.

In addition to the business-related characteristics, cooperative banks also maintain a special supervisory board structure regarding the occupational background. Due to the size and regional focus members of the supervisory board are often local entrepreneurs, politicians and other significant personalities. Cooperative banks in Germany developed from two different sub-types. One focused on merchants while the other focused on farmers. This historical development also appears in the occupational background of supervisory board members. According to the study sample about 20% of supervisory board member are full-time farmers. The potential influence and whether this percentage remained consistent after the application of the FinVAG is one main issue of the current study.

4.2.2 FinVAG

The distortions following the financial crisis in 2007 made it apparent that regulators and legislators have to implement stricter rules and principles to ensure a higher level of stability in the international finance sector (Crotty, 2009). In the aftermath many of such rules were adopted.[63] One of it being the German Act to Strengthen Financial Market and Insurance Supervision (FinVAG) in 2009. The FinVAG focused on the further empowerment of BaFin, which is henceforward capable of setting higher equity- and liquidity requirements and enforcing the disclosure of risk-concentration. The capacities mentioned before are beyond doubt important and affect management behavior. However, more important for this study is the authorization to control the supervisory board and initiating an impeachment regarding unqualified members of the supervisory board.

According to the FinVAG, members of the supervisory board are qualified to fulfil their function, if they are reliable, adequately qualified and capable of evaluating and overseeing the bank's business justifiably. When in doubt, BaFin may initiate an audit procedure which is announced publicly taking into account the level of complexity of bank's business (which may differ to a great extent). If the suspicion is confirmed, BaFin is empowered to demand the dismissal of involved board member or the prohibition of further exercise of the activity. If the supervisory board does not comply with the demand, BaFin is also empowered to initiate the impeachment via court without consent of the supervisory board.

Although the characteristics which define whether board members are qualified or not are vague[64], the implementation of FinVAG was not without consequences. Until the end of august, 2010, ten dismissal procedures were initialized.

4.3 Literature and Hypotheses

4.3.1 Literature review

Literature regarding governance issues is divisible into two questions, which researchers try to answer. First, what determines board characteristics and

[63] For an overview regarding German and European regulatory efforts, see BMF (2014).

[64] This changed in new iteration of the FinVAG, as more and more strictly defined characteristics were included in the law text. However, these changes are not relevant for the study, as the sample period ends in 2011.

structure? Second, how do board characteristics influence important banking characteristics like performance or risk? Since the present study tries to gain insights in both topics a short overview of both literature streams is necessary.

With respect to determinants of board characteristics literature considers various factors to be important e.g. ownership structure, banking model, legal and regulatory environment. However, results vary substantially and depend on the industry and situation (e.g. Mak and Li 2001; Baker and Gompers, 2003; Linck et al., 2008; Pathan and Skully, 2010). Therefore, it is important to understand that the optimum board composition relies on various factors, hence should not be regulated uniformly (Coles et al., 2008; Andres et al., 2012). Certainly, the aforementioned authors focus their research on factors which influence the board structure due to pressure from outside of the bank. However, some authors consider the signalling theory which describes the process used by decision makers in absence of certainty.[65] In line with Spence (1973) they interpret board characteristics not only as a result of outside pressure, but as a signal of beneficial corporate properties to shareholders and regulators. Certo et al. (2001) investigate the signalling effect of board characteristics as reputation and size on the extent of under-pricing during initial public offering (IPO). Their results indicate that board reputation and size decrease under-pricing as these characteristics reduce uncertainty.[66]

Literature which focuses on the effects of board characteristics is often interested in three topics: general governance issues and the impact on performance and risk. Especially literature regarding governance issues and performance is well developed. Agrawal and Chadha (2005) showed for a sample of 159 U.S. listed companies that independency and financial expertise of boards and audit committees are key factors when it comes to preventing accounting scandals. Regarding financial expertise various studies (e.g. Kroszner and Strahan, 2001; Byrd and Mizruchi, 2005) investigate the behaviour of bankers in non-banking boards and come to different results concerning the capability of monitoring while being subjected to potential conflicts of interest. Byrd and Mizruchi (2005) find that bankers representing lender banks only exercise monitoring functions, while non-

[65] Spence (1973) formulated signal theory to explain the relationship between employers, potential employees and their educational information on labour markets.

[66] Connelly et al. (2011) summarized meaningful literature regarding signaling theory in their comprehensive literature review.

lender bankers alter their behaviour in accordance to the state of the company. They engage in a monitoring role when companies are economically sound while shifting to a more consultatively role during financial distress. Another question which is discusses in financial and non-financial literature is if there is a universal optimal board composition. For non-financial firms, the study of Coles et al. (2008) find evidence for a U-shaped relationship between board size and Tobin's Q, hence either small or big boards being optimal. Furthermore, the optimal degree of independency is related to the extend in which firms are R&D-dependent. While there is a broad stream of literature related to general governance issues and bank performance, literature regarding risk-taking is not as well developed and often limited to capital regulation, charter value, market discipline and ownership structure. Pathan (2009) investigates American banks during the period 1997-2004. The results indicate that small boards are related to higher risk taking. He reasons that small boards are more capable of fulfil their function as representatives of shareholders who have preferences for higher risk-taking. Contrary to this "strong board" reasoning, his results indicate a negative relationship between independent directors and risk-taking, thus indicate a true independence of directors from firm and shareholder interests. Independent directors seem to focus on the regulatory function. Finally, Pathan (2009) finds evidence for a negative impact of CEO power on risk-taking. This finding is in line with expectations as CEOs prefer a lower risk profile due to their asset concentration on the firm, especially human capital. The results regarding independent directors are confirmed for the Taiwan banking market by the study of Ting and Liao (2010). Their findings indicate that shareholders use their increase in power after poor firm performance to select more affiliated directors which impact the nonperforming loans ratio in a positive way, hence increasing risk exposure. These results are also confirmed by Beltratti and Stulz (2012) who find that board's shareholder-friendliness is coherent with higher risk exposure.

There are also studies which address other times of bank risk than traditional measures as credit risk or Z-Score. Wang and Hsu (2013) investigate the relationship between the board composition and the probability of operational risk events motivated by the recent focus of the Basel Committee on non-credit risks. Their study shows evidence that an increase in total board members is beneficial, hence decreasing the likelihood of operational risks. However, their analysis goes one step further and considers non-linearity. Their results show that an increase in board members is still beneficial, but with diminishing effects. After exceeding the number of 14 board members the effect goes into reverse and any additional member increases the probability of operational risk events.

Most studies regarding board characteristics and the influence on risk focus their research on aggregated data like board size. However, the present study tries to shed some light on more in-depth characteristics like Ph.D. share and occupational background. Concerning the Ph.D. share which can be interpreted as high education and its influence on risk previous studies do not reveal a clear coherence. Christiansen et al. (2008) show that private investment in stock markets increases with the level of education, hence indicating a risk-increasing influence. Regarding business choices Bertrand and Schoar (2003) show that MBA holders are more aggressive and relate to a higher leverage, thus a higher risk. On the other hand, Graham and Harvey (2001) find evidence for a risk-decreasing effect of a higher education. They reason, based on their survey that MBA holders tend to employ more sophisticated techniques frequently, thus decrease risk due to their technical advantage. Berger et al. (2012) share this reasoning for their study on German banks and find evidence for the risk-reducing influence.

When it comes to occupational concentration literature discusses various aspects.[67] The first aspect is that an increase in diversification may improve the decision-making process. Authors like Alvarez and McCaffery (2000), Carpenter and Westphal (2001) and Hutchinson et al. (2015) suggest that diversity results in more and higher developed ideas and alternatives due to the different perspectives related to the occupational background. On the other hand, these different perspectives may also lead to problems in situations when important decisions regarding the future are taken. Goodstein et al. (1994) show that diversification decreases the likelihood of strategic changes in hospitals. This result is strengthened by Hambrick et al. (1996) who find that an increase in heterogeneity regarding group composition leads to more disagreement between members, hence a weaken board consensus and therefore more problems when it comes to dealing with major problems.

[67] It is noteworthy, that literature mainly focuses on gender and nationality diversity. However, the underlying relationships are also applicable on occupational diversity.

4.3.2 Research Hypotheses regarding board structure

With the implementation of FinVAG BaFin gained the authorization to intervene regarding the composition of the supervisory board. This may occur if BaFin is not sure that certain members of the board are fully capable of understanding the banking business, thus are unable to carry out their control function. In this case BaFin will initiate an investigation which is announced publicly. This sole announcement is connected with a potential loss in reputation as a supervisory board which does not provide sufficient control capability is not able to detect harmful management behavior (e.g. Agrawal and Chadha, 2005). In that case the management may engage in moral hazard behavior and pursue short term performance at a cost of future stability as it may cut credit screening and monitoring expenses. These measures impact the short-term profitability positively but lead to a higher risk exposure regarding the quality of the credit portfolio. Alternatively, the management may not be able to handle the bank's business correctly due to a lack of competence and knowledge (e.g. Fiordelisi et al., 2011). This bad management may be revealed by competent supervisors but may be unobservable by less competent members. These consequences may even be strengthened if the management is aware of the competence level of the supervisory board. For these reasons a potential loss of reputation due to the announcement of a control procedure by BaFin is possible and therefore desirable to prevent.

As a result, there are two measures to prevent audit procedures and the loss of reputation accordingly. First, banks may invest in their supervisory board enabling them to fulfil the requirements of a qualified supervisor. This measure is costly, time-consuming and highly dependent on the initial level of competence. Alternatively, banks may replace supervisory board member who may cause audit procedures in advance. This measure is in most cases more favorable as it is related to less cost and effort and is independent of the competence. As both measures require some lead time as they have to be carried out prior to or shortly after the implementation of FinVAG in 2009. Based on the relationships, I postulate the hypothesis within this context as:

> **H1: The implementation of FinVAG may increase the number of supervisory board changes in 2009.**

Closely connected to the actual number of supervisory board changes is the resulting supervisory board structure. In this study, I focus my research on the share of Ph.D. degree holders and the occupational background of supervisory board members as both attributes are highly related with the understanding of banking business. It is highly likely that the potential understanding of a complex business like banking is higher when the regarded board member holds a Ph.D. degree. The reason for this derives from the implicitly higher academic education, which is obtained in most instances by analyzing complex coherences, regardless of the field in which the Ph.D. was obtained (Hau and Thum, 2009). It is therefore possible that a Ph.D. degree has an inherent signalling function which may affect the perception of BaFin regarding the actual competence. In that case members with Ph.D. degrees are preferred in contrast to members without Ph.D. degrees. That should be especially relevant in cases of new appointments. It is for this reason, that I postulate the hypothesis regarding the development of Ph.D. shares as:

> **H2: The implementation of FinVAG may increase the share of supervisory board members who hold a Ph.D. degree.**

The occupational background of supervisory board member may also have a signalling function, comparable to the effect of a Ph.D. degree. Due to the origin of cooperative banks and their local focus supervisory boards often consists of well-known and important persons within the area of operation. For these reasons the occupational background differs to a large extend and ranges from entrepreneurs, economists and lawyers to farmers, craftsmen and persons in various political offices, with farmers, craftsmen and entrepreneurs forming the largest proportion. It is clear that these different occupational backgrounds are related to the potential and actual understanding of banking business (Kesner, 1988). In this context I assume that an economic-educational background, whether on an academic level or not, is related to a higher potential understanding of banking key figures in regard to risk and performance. This higher potential understanding may then exert a similar signaling function as a Ph.D. degree. Therefore, I expect that in the event of a board change shortly prior or after the implementation of FinVAG, there is an incentive to favor personnel with an economic background. It is for this reasons that I postulate the hypotheses regarding the occupational background as:

H3a: The implementation of FinVAG may increase the share of supervisory board members who have an economic background.

H3b: After the Implementation of FinVAG a retiring supervisory board member without economic background may be succeeded by a person with an economic background.

Closely connected to the hypotheses regarding occupation background is the development of the occupational concentration in supervisory boards. As mentioned before the signalling function of economic background and, to some extent, Ph.D. degree, put occupations in the economic sphere in a favourable position when it comes to the replacement of supervision board members. This should lead to an increase in occupational concentration in the period shortly before and after the implementation of FinVAG. Therefore, I postulate the hypotheses regarding the occupational concentration as:

H4: The implementation of FinVAG may increase the occupational concentration of supervisory boards.

4.3.3 Research Hypotheses regarding relationships between board characteristics and risk

Regarding the relationship between risk measures and board characteristics the study focuses mainly on Ph.D. share and occupational concentration. Regarding these relationships I expect the effects to be in line with previous literature regarding Ph.D. share, occupational concentration and other regulatory interventions like the implementation of Sarbanes-Oxley (SOX) (e.g. Akhigbe and Martin, 2008; van Ness et al., 2010).

As discussed above literature regarding the link between educational level and risk-taking is rather inconclusive. Some results indicate a risk decreasing effect (e.g. Graham and Harvey, 2001; Berger et al., 2012) while some findings point to a risk increasing effect (e.g. Bertrand and Schoar; 2003). Therefore, I postulate the hypotheses regarding the effect of the Ph.D. share during the pre-FinVAG period as:

H5a: An increase in Ph.D. share may reduce risk exposure.

H5b: An increase in Ph.D. share may increase risk exposure.

The effect of Ph.D. share should be clearer in the period after the implementation of FinVAG. As mentioned before, members of the supervisory board may lose their position, if BaFin is not sure about the control capabilities of certain members. Due to the positive signalling function of Ph.D. degree holders (see H2) they may be the first to be in doubt regarding their control function. Hence, Ph.D. degree holders have a strong incentive to prevent investigation which may be caused by high risk exposure. Consequently, I postulate the hypothesis regarding the effect of Ph.D. share after the implementation as:

H5c: After the implementation of FinVAG an increase in Ph.D. share may reduce risk exposure.

As with literature regarding the effect of Ph.D. degree holders literature regarding occupational concentration is also inconclusive. Some studies find evidence that an increase in perspectives lead to better decisions (e.g. Carpenter and Westphal, 2001), while others point to problems due to the heterogeneity which result in more disagreement between members (e.g. Hambrick et al., 1996). Therefore, decisions regarding risk-related issues could be facilitated or impeded, based on which effect prevails. Consequently, the hypotheses regarding the effect of occupational concentration is postulated as:

H6a: An increase in occupational concentration may reduce risk exposure.

H6b: An increase in occupational concentration may increase risk exposure.

The expectations regarding the effect of occupational concentration are in line with the effect of Ph.D. degree holders in the post-FinVAG period. As member of the supervisory board are now subject to the opinion of BaFin, they are now incentivized to act in a risk-reducing way. Therefore, the probability of disagreement and prolonging risk-related issues should decrease. Consequently, the hypothesis regarding the effect of occupational concentration after the implementation of FinVAG is postulated as:

H6c: After the implementation of FinVAG an increase in occupational concentration may reduce risk exposure.

4.4 Data and Methodology

4.4.1 Data

The present dataset is based on hand collected annual balance sheet, board structure and income statement data of 336 Bavarian cooperative banks from 2006 to 2011. Regarding the board structure data is available for gender as well as occupational background. In this study I focus on occupational background, gender is only mentioned in passing. Although there are studies that investigate gender in terms of board structure (e.g. Miller and del Carmen Triana, 2009; Berger et al., 2012) the main focus of the current study lies in the signalling function of certain occupation and education level. This competence related signalling function is not expected to be triggered by gender.

The examined dataset is present in a balanced panel and consist solely of banks with no M&A activities during the sample period. The reasoning behind this exclusion is based on results of Pathan and Skully (2010) who find that board sizes frequently rises subsequently to bank mergers. This would cause distortions regarding all relevant board-related variables as they are scaled by total board size.[68] As a result the final data set consists of 246 cooperative banks. Table 4.1 summarizes the data set modifications

Table 4.1

Sample Selection

Initial sample of Bavarian cooperative banks with balance sheet and income statement data from 2006 to 2011 (Source: German "Bundesanzeiger")	336 banks
Exclusion of banks which were actively or passively participating in a merger between 2006 and 2011	-90 banks
Final Sample	246 banks
	1476 Observations

[68] Additional to the explained reason, mergers would interfere in the analysis of board structure, as they are not intended changes in board structure. These changes are byproducts of the mergers and thus not intended.

4.4.2 Methodology

To investigate the aforementioned hypothesis the study employs two different procedures. In a first step, the study employs t-test to examine the hypotheses regarding board structure changes. T-tests are able to determine whether differences in means between two unpaired groups are significant. In the second step, I use the System GMM estimator based on Arellano and Bover (1995) and Blundell and Bond (1998), which is capable of disentangling the rather unclear relationship between board characteristics and risk measures. Furthermore, the introduction of lagged variables, e.g. the dependent variable in t-1, is often related to endogeneity problems. These endogeneity problems cause coefficients obtained by OLS-estimation to be upward biased while fixed-effect-estimation result in a downward bias (when $T \rightarrow \infty$ is not given). Regarding system GMM the time-related problem persists and causes standard errors to be downward biased, resulting in an overstatement of significances. Therefore, the study also employs the standard error correction for finite sample panels developed by Windmeijer (2005).

In the result section, AR(1), AR(2) and Hansen-statistics are also reported. For a valid regression and therefore interpretable coefficients, all three statistics must be within reasonable limits. The AR(1) test should indicate a significant correlation between t-1 and t-2 differences. For AR(2) and Hansen-test both test-statistics should indicate insignificant results. However, according to Wintoki et al (2012) both test-statistics should not be judged under the assumption of "conventional levels" as these may lead to failures in detecting misspecifications. On the other hand, a p-value near 1 for Hansen-test also indicate that the Hansen-test fails to be conclusive as this result is often related to a high number of instruments, which weakens the validity of the test (Roodman, 2009).

4.5 Variables Description and Descriptive Statistics

As mentioned before, this study tries to find evidence regarding the effect of FinVAG on the supervisory board structure as well as on the relationship between various competence related board characteristics and risk measures which are also focused on by FinVAG.[69]

4.5.1 Structural Changes

For the investigation of board structure related issues, the study uses shares of occupational background in the supervisory board. As a very detailed analysis of occupational backgrounds would not be expedient. I clustered occupational backgrounds regarding competence in two different levels of aggregation. For instance, there is a differentiation between auditors and tax advisors on the more detailed level. On the more aggregated level both groups form an accumulated group as the intersection of competence is large. In addition, very small and only rarely occurring occupation grounds with no special financial knowledge are pooled in the group “other”.[70]

4.5.2 Board Characteristics

To investigate the coherences between board characteristics and risk measures the study focuses on four different bank risk measures, two competence related board characteristics and various control variables. For risk measures the study follows mainly FinVAG and its indented function. To depict credit risk the study uses loan loss provisions (LLP). This proxy for credit risk is not unproblematic as LLP might be manipulated by managers in order to engage in earnings management (e.g. Beatty and Liao, 2014). However, other measures for credit risk are not available for German cooperative banks during the investigated period. To address capital risk and therefore the risk of bankruptcy the study uses the equity to asset ratio (CAP). As a robustness test the study also employs a deviating equity to asset ratio (CAP_a), which also contains capital with equity properties. To investigate relationships with liquidity (LIQ) the study employs a measurement based on Radić (2015) which is defined as the ratio between short-term assets and funding. The last risk measurement is not addressed in FinVAG but is often used to depict overall

[69] All variables are summarized in appendix 4.A.

[70] Appendix 4.B summarizes the occupational backgrounds and groups based on both aggregation levels.

bank risk, hence is used to check if the results are in line with the overall risk. To address this overall risk the study employs the commonly used Z-Score (ZS).

As mentioned before, the study focuses on competence related board characteristics. The considered variables are the share of Ph.D. holders in the supervisory board (PHD) and the occupational concentration (CON). To calculate the occupational concentration, the study applies the Herfindahl-Hirschman Index for concentration:

$$CON = \left(\frac{A}{TOTAL}\right)^2 + \left(\frac{B}{TOTAL}\right)^2 + \cdots + \left(\frac{Z}{TOTAL}\right)^2 \qquad (1)$$

whereas the numerator contains the number of board member of a certain occupational group and the denominator the total number of board member. As with capital risk occupational concentration in defined in two different levels of detail with CON_a being the broadly defined one. CON_a is used as a robustness test to verify that results are not driven by technical issues. In addition to competence related characteristics supervisory board power (SBP) is also included. SBP is calculated as the ratio between the number of supervisory board and executive board members as cooperative banks have two-tier boards. To account for the implementation of FinVAG two different effects are considered. First, I include the variable FIN to account for the overall effect of FinVAG which is a dummy variable that equals "one" in the years 2009, 2010 and 2011. Additionally, I include interaction terms for the aforementioned board characteristics to account for the effects of FinVAG especially on theses variables.

Eventually, I added control variables which are common in banking and board related literature. The equity to asset ratio (CAP) accounts for differences in leverage and therefore risk preferences. To consider magnitude effects regarding risk-measurements I add the logarithm of total assets (TA). The income diversification (ID) is measured as the ratio between non-interest income and total income. It also highlights risk preference aspects of the management as non-interest income is often higher in value but more volatile. Hence banks with more non-interest income may possess a different risk structure. Finally, the variables GDP-

Growth (ΔGDP), interest rate ($INTRATE$)[71] and unemployment rate ($UNEMP$) control for macroeconomic effects.

Based on the aforementioned variables the study employs the following regression models via System GMM estimation:

$$\begin{aligned} RISK_{i,t} = \alpha + \beta_1 RISK_{i,t-1} + \beta_2 PHD_{i,t} + \beta_3 CON_{i,t} + \beta_4 SBP_{i,t} + \beta_5 FIN \\ * PHD_{i,t} + \beta_6 FIN * CON_{i,t} + \beta_7 FIN * SBP_{i,t} + \beta_8 FIN_{i,t} \\ + \{\beta_9 CAP_{i,t}\} + \beta_{10} TA_{i,t} + \beta_{11} ID_{i,t} + \beta_{12} \Delta GDP_t \\ + \beta_{13} INTRATE_t + \beta_{14} UNEMP_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

i denotes each bank and t is the time period (2006, 2007…,2011). α is the constant, β_{1-14} are the coefficients to be estimated via system GMM estimator, $\varepsilon_{i,t}$ is the disturbance term. In the four regressions models the variable $RISK_{i,t}$ is either LLP, CAP, LIQ or ZS. When $RISK_{i,t}$ is replaced with CAP, the right-hand side variable CAP is omitted. As mentioned before all board characteristics are also interacted with the FinVAG dummy to account for changes in the effect on the risk measures.

4.5.3 Descriptive statistics

Table 4.2 contains descriptive statistics regarding the board characteristics and the investigated occupational backgrounds.[72] The mean supervisory board size ($TOTAL$) amounts to 6.77, with the median supervisory board consisting to 6 persons. Based on standard deviation, minimum and maximum it is obvious that the number of supervisory board member is notably heterogeneous, with the smallest supervisory board consisting of only 2 members while the biggest one consists of 29 members. The $CHANGE$ variable shows that in every year 31% of investigated cooperative banks have changed their board structure by varying the total number or composition regarding occupational background. On average 4.55% of board members are female, with 40% being the highest share. Regarding the occupational groups it is apparent that farmers form the biggest proportion (beside "others"), followed by non-business employees and entrepreneurs.

[71] The ECB interest rate is calculated as daily weighted values for each year.

[72] For reasons of clarity, descriptive statistics and further analysis of occupational backgrounds are based on aggregated levels. However, results do not differ substantially.

Table 4.2

Descriptive statistics of board characteristics and occupational groups

	Mean	Median	Std. Dev.	Min	Max
TOTAL	6.772	6	3.423	2	29
CHANGE	0.314	0	0.464	0	1
FEMALE	0.046	0	0.087	0	0.4
TAXA	0.044	0	0.084	0	0.4
EMP	0.148	0.111	0.177	0	1
CLERK	0.115	0	0.158	0	0.778
ENT	0.124	0	0.167	0	0.8
LAW	0.024	0	0.067	0	0.4
MED	0.017	0	0.056	0	0.4
ENGI	0.056	0	0.100	0	0.6
FARM	0.207	0.167	0.200	0	1
POL	0.053	0	0.102	0	0.667
PROF	0.003	0	0.020	0	0.2
OTH	0.209	0.167	0.198	0	1

In table 4.3 these figures are broken down into year-based figures to analyse the progression of means. In this depiction it becomes apparent that the total number of board members decreases steadily over time from 7.252 to 6.447 members from 2006 to 2011. This development extends to the board structure changes. While 35% of supervisory boards changed in structure or total number from 2006 to 2007, only 26.8% changes from 2010 to 2011. An opposite development is observable regarding the female share of supervisory board member. This share is increasing steadily from 3.4% in 2006 to 5.6% in 2011. Regarding the occupational backgrounds it comes apparent that most groups increased their share from 2006 to 2011 at a cost of shares of farmers and “other” occupational backgrounds. This may be a first indicator of how the implementation of FinVAG may influence decisions regarding the choice of board member.

Table 4.3

Development over time of aggregated occupational groups and other board characteristics.

	2006	2007	2008	2009	2010	2011	total
TOTAL	7.252	7.028	6.805	6.618	6.484	6.447	6.772
CHANGE	.	0.350	0.325	0.317	0.309	0.268	0.314
FEMALE	0.034	0.039	0.045	0.048	0.052	0.056	0.046
TAXA	0.039	0.045	0.044	0.045	0.046	0.047	0.044
EMP	0.143	0.146	0.147	0.149	0.148	0.151	0.148
CLERK	0.108	0.110	0.113	0.118	0.118	0.122	0.115
ENT	0.112	0.117	0.120	0.124	0.133	0.141	0.124
LAW	0.021	0.023	0.024	0.025	0.025	0.028	0.024
MED	0.015	0.016	0.018	0.017	0.018	0.020	0.017
ENGI	0.057	0.058	0.057	0.056	0.054	0.053	0.056
FARM	0.221	0.218	0.214	0.204	0.196	0.186	0.207
POL	0.051	0.051	0.051	0.053	0.054	0.055	0.053
PROF	0.002	0.002	0.003	0.003	0.003	0.004	0.003
OTH	0.230	0.214	0.210	0.205	0.204	0.193	0.209

Table 4.4
Summary statistics of the variables of interest

	Mean	Median	Std. Div.	Min	Max
Panel A: Risk measures					
LLP	0.006	0.005	0.005	-0.020	0.039
CAP	0.060	0.058	0.013	0.026	0.119
LIQ	0.248	0.212	0.153	0.018	2.054
ZS	4.157	4.010	0.836	1.776	7.834
Panel B: Board structure variables					
DRAR	0.0314	0	0.078	0	0.6
CON	0.3175	0.28	0.142	.111	1
SBP	3.015	2.667	1.494	.571	13.5
Panel C: Control variables					
TA*	343.214	230.250	407.957	21.053	4.607.324
ID	0.264	0.259	0.103	-1.325	0.651

*in billion Euro

Table 4.4 contains descriptive statistics of the variables which are regarded in the regression model. The mean *LLP* comprises 0.58% of the loan portfolio. The minimum is negative, hence indicating more appreciations than depreciations. The mean equity to asset ratio is 6.0% while varying strongly between 2.6% and 11.9%. The same statement holds true for the liquidity ratio which varies between 1.7% and 205.4%, with the mean comprising 24.8%. Z-Score values reflect the overall high financial stability of cooperative banks. A mean Z-Score of 4.16 and a minimum of 1.78 show that even low capitalized banks possess a sufficient buffer. Regarding the focused board structure figures, supervisory board in cooperative banks have a 3.1% share of Ph.D. holder on average with the maximum being 60%. The values for occupational concentration indicates that the average supervisory board is rather diversified, but there are banks with complete concentration on one occupational background. The supervisory board power variable shows that on average about 3 supervisory board members oversee the actions of 1 executive board member. This figure has a high volatility with one supervisor for two executive members to 13.5 supervisors for one executive board member. Total assets indicate that the sample comprises small and medium sized banks with a range of total assets from 21 million euro up to 4.6 billion euro. On average, cooperative banks earn 26.4% of their income by non-interest activities.

Table 4.5 shows the development over time of the variables mentioned before. When considering the development over time it comes apparent that *LLP* decreased from 2006 to 2011. An even stronger decrease is displayed by the liquidity ratio which almost halves from 2006 to 2011. On the other side the equity to asset ratio as well as the Z-Score remain the same over time. Regarding board structure variables the share of Ph.D. holders and the occupational concentration slightly increase over time, while supervisory board power decreased. Regarding bank control variables it becomes clear that the investigated cooperative banks increase in size and shifted they income focus away from non-interest activities to interest generating ones.

Table 4.5

Development over time of relevant regression variables (means)

	2006	2007	2008	2009	2010	2011	total
Panel A: Risk measures							
LLP	0.009	0.006	0.006	0.004	0.005	0.004	0.006
CAP	0.061	0.061	0.059	0.059	0.060	0.062	0.060
LIQ	0.335	0.286	0.263	0.237	0.187	0.177	0.248
ZS	4.180	4.159	4.117	4.145	4.167	4.177	4.157
Panel B: Board structure variables							
$DRAR$	0.027	0.030	0.033	0.032	0.033	0.034	0.031
CON	0.309	0.312	0.317	0.323	0.324	0.320	0.318
SBP	3.107	3.048	3.074	3.009	2.933	2.917	3.015
Panel C: Control variables							
TA	3.050	3.170	3.360	3.530	3.640	3.840	3.430
ID	0.355	0.301	0.258	0.241	0.216	0.215	0.264

Table 4.6 shows the Pearson's pairwise correlations between variables investigated in the regression. All board structure variables (PHD, CON and SBP) are significantly correlated with total assets. Therefore, indicating that larger banks have more Ph.D. holders, a greater ratio between supervisory board members and executive board members and are also less concentrated regarding occupational background. The correlations also show that banks with more non-interest income have a less concentrated board and simultaneously a higher supervisory board power. The correlation between SBP and TA (0.54) display that multicollinearity might be an issue. However, testing this concern with the variance inflation factor test (VPI) results in a mean VPI of 1.30 which is well below the threshold of 10.[73]

[73] When interactions terms are included in VPI test, the resulting mean VPI is 4.26 which is also below the aforementioned threshold.

Table 4.6

Correlation Matrix regarding relevant regression variables

	LLP	CAP	LIQ	ZS	PHD	CON	SBP	FIN	TA*	ID
LLP	1.000									
CAP	-0.000	1.000								
LIQ	0.10***	0.10***	1.000							
ZS	0.03	-0.06**	-0.06**	1.000						
PHD	0.015	-0.11***	-0.09***	0.05*	1.000					
CON	-0.002	0.041	0.11***	-0.08***	-0.06**	1.000				
SBP	0.05**	-0.14***	-0.23***	0.024	0.06**	-0.31***	1.000			
FIN	-0.25***	0.010	-0.31***	0.007	0.023	0.033	-0.041	1.000		
TA	-0.034	-0.4***	-0.33***	-0.028	0.23***	-0.25***	0.54***	0.07***	1.000	
ID	0.35***	-0.029	0.046*	-0.011	0.001	-0.09***	0.10***	-0.39***	0.10***	1.000

4.6 Empirical Results

4.6.1 Structural Changes in Supervisory Board Alignment

Table 4.7 shows the results for t-tests which are conducted to investigate hypotheses 1-4. For the variable $CHANGE$ the difference between the means during pre-FinVAG and post-FinVAG is not significant. This implies that the implementation of FinVAG did not increase the number of changes in board structure, hence speaking against H1. The same is also true for H2 and H4 as the share of Ph.D. holders as well as occupational concentration do not increase significantly in post-FinVAG period. The only characteristics which increase significantly is the share of female supervisors in the post-FinVAG period. These results hold true for broader or narrower time frames regarding post-FinVAG period. Regarding occupational background, results indicate, that the group of entrepreneurs significantly increased, while farmers and other job group significantly decreased. This may be evidence for H3a.

Table 4.7

Comparison of board characteristics and occupational backgrounds pre- and post-FinVAG

	Pre-FinVAG		Post-FinVAG		Difference t-test P-Value
	Obs.	Mean	Obs.	Mean	
Board characteristics					
CHANGE	492	0.337	738	0.298	0.146
PHD	738	0.027	738	0.033	0.387
CON	738	0.313	738	0.322	0.202
SBP	738	3.076	738	2.952	0.113
FEMALE	738	0.039	738	0.052	0.004***
Occupational Background					
TAXA	738	0.042	738	0.046	0.405
EMP	738	0.145	738	0.147	0.638
CLERK	738	0.110	738	0.120	0.248
ENT	738	0.116	738	0.133	0.055*
LAW	738	0.023	738	0.026	0.322
MED	738	0.017	738	0.018	0.521
ENGI	738	0.057	738	0.054	0.536
FARM	738	0.218	738	0.196	0.031**
POL	738	0.051	738	0.054	0.601
PROF	738	0.002	738	0.003	0.326
OTH	738	0.218	738	0.201	0.090*

Table 4.8

Correlation matrix for changes between occupational groups

	C.TAXA	C.EMP	C.CLERK	C.ENT	C.LAW	C.MED	C.ENGI	C.FARM	C.POL	C.PROF	C.OTH
C.TAXA	1.000										
C:EMP	-0.02	1.000									
C.CLERK	-0.22***	-0.02	1.000								
C.ENT	0.08***	-0.13***	-0.16***	1.000							
C.LAW	0.000	0.02	-0.02	0.05**	1.000						
C.MED	0.05*	-0.10***	0.04*	0.02	-0.05*	1.000					
C.ENGI	0.03	-0.08***	-0.08***	-0.02	-0.03	-0.07***	1.000				
C.FARM	-0.003	-0.07***	0.01	-0.10***	-0.01	-0.04	-0.04*	1.000			
C.POL	0.03	-0.06**	-0.05*	0.01	-0.12***	0.10***	-0.06**	-0.01	1.000		
C.PROF	-0.12***	-0.06**	0.16***	0.10***	-0.0005	-0.001	-0.08***	0.01	0.002	1.000	
C.OTH	0.06**	-0.08***	-0.11***	-0.15***	-0.06**	-0.09***	-0.03	0.03	-0.06**	-0.04	1.000

*in Million Euro

To investigate H3b stating that non-financial occupational backgrounds are replaced by financial backgrounds I use Pearson's pairwise correlations between occupational change variables summarized in Table 4.8. The variables $C.[occupation\ group]$ represents the changes in numbers of members with a certain occupational background from year t-1 to t. Hence, when no change in number occurs the variable equals zero, otherwise it is a positive or negative integer number. Regarding the results there are some interesting correlations which support Hypothesis H3b. Entrepreneurs and farmers correlate negatively. It follows that when the share of one increases the other decreases. In combination with results summarized in table 4.7 this means that farmers were in fact substituted by entrepreneurs which is evidence for H3b. Further evidence for H3b is the negative correlation between entrepreneurs and other job-groups. In addition to these strong evidences which are supported by results of table 4.8 there are negative correlations between clerks and other job-groups and between entrepreneurs and non-financial employees.

Table 4.9 shows an alternative correlation matrix. These correlations are based on changes in which the total number of supervisory board members remained the same, thus representing actual member exchanges. Although correlations change in this version the main implications regarding Hypothesis H3b remain the same. Entrepreneurs substitute non-financial employees, while clerks substitute farmers and politicians. Consequently, Hypotheses H3b is also support by these findings.

Table 4.9

Correlation matrix for changes between occupational groups (exchanges only)

	C.TAXA	C.EMP	C.CLERK	C.ENT	C.LAW	C.MED	C.ENGI	C.FARM	C.POL	C.PROF	C.OTH
C.TAXA	1.000										
C:EMP	0.004	1.000									
C.CLERK	-0.32***	-0.18*	1.000								
C.ENT	0.12	-0.26**	-0.23**	1.000							
C.LAW	-0.15	-0.01	-0.15	0.11	1.000						
C.MED	0.01	-0.08	-0.01	-0.03	-0.01	1.000					
C.ENGI	-0.15	-0.24**	0.06	-0.20*	-0.17	-0.15	1.000				
C.FARM	-0.16	-0.16	-0.21**	-0.07	0.03	-0.09	-0.06	1.000			
C.POL	0.24**	0.12	-0.23**	-0.01	-0.01	-0.01	-0.26**	-0.10	1.000		
C.PROF	0.004	-0.20**	-0.01	-0.02	-0.01	-0.02	-0.01	0.03	-0.01	1.000	
C.OTH	-0.067	-0.06	-0.08	-0.45***	-0.17	-0.13	-0.08	-0.20**	-0.18*	0.03	1.000

*in Million Euro

4.6.2 Influence of Board Structure in consideration of FinVAG

Table 4.10 – 4.12 summarize the regression results regarding the influence of board structure on risk measurements in consideration of the effect of FinVAG. In table 4.10, the occupational groups which are used to calculate occupational concentration are less aggregated. All four risk measures are positively influenced by their respectively level in the period t-1. During the time frame before the implementation of FinVAG the share of Ph.D. holders increased the exposure to credit risk (positive effect in column 1), capital risk (negative effect in column 2) and total risk measure (negative effect in column 4).

Table 4.10

Regression results for the relationship between board characteristics and risk measures

VARIABLES	(1) LLP	(2) CAP	(3) LIQ	(4) ZS
L.LLP	0.092**			
	(0.043)			
L.CAP		1.071***		
		(0.036)		
L.LIQ			0.590***	
			(0.150)	
L.ZS				0.995***
				(0.011)
PHD	0.045**	-0.061*	-0.132	-0.165*
	(0.021)	(0.035)	(0.137)	(0.088)
CON	0.021**	-0.027	0.975**	-0.456
	(0.010)	(0.020)	(0.418)	(0.295)
SBP	0.000	-0.001*	0.023*	-0.048***
	(0.000)	(0.001)	(0.013)	(0.014)
FIN*PHD	-0.048**	0.083**	0.258**	0.155*
	(0.021)	(0.034)	(0.109)	(0.081)
FIN*CON	-0.024**	0.040*	-0.989	0.570*
	(0.010)	(0.020)	(0.414)	(0.293)
FIN*SBP	-0.001*	0.001*	-0.022*	0.041**
	(0.000)	(0.001)	(0.012)	(0.017)
FIN	-0.016*	0.012	0.552**	-0.023
	(0.009)	(0.012)	(0.239)	(0.186)
CAP	0.060*		0.607	0.634
	(0.033)		(0.650)	(0.730)
TA	0.001	0.002*	-0.037	0.048*
	(0.001)	(0.001)	(0.024)	(0.025)
ID	0.018***	-0.023**	-0.089	-0.230*
	(0.003)	(0.012)	(0.237)	(0.123)
ΔGDP	-0.017**	0.039***	-0.028	0.228
	(0.007)	(0.009)	(0.200)	(0.147)
INTRATE	-0.947***	1.007***	7.889	8.425**
	(0.232)	(0.277)	(6.814)	(4.291)
UNEMP	-0.059**	0.191***	0.067	2.284***
	(0.029)	(0.046)	(1.195)	(0.684)
Constant	0.015	-0.079***	0.107	-1.122*
	(0.022)	(0.027)	(0.615)	(0.651)
Wald Chi2	117.64***	2,181.61***	342.32***	23,466.84***
AB test AR(1)	-5.99***	-4.22***	-4.03***	-5.79***
AB test AR(2)	1.08	1.09	1.29	0.27
Hansen test, 2nd step	69.21	37.54	22.08	71.53
No. of Instruments	78	49	46	78
No. of Groups	246	246	246	246
No. of Observations	1,230	1,230	1,230	1,230

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The share of Ph.D. holders in the pre-FinVAG period also increases the exposure to liquidity risk yet not significantly. These results support Hypothesis H5b which implies a risk-increasing effect of Ph.D. holders due to their risk affinity. After the implementation of FinVAG the aforementioned effect ceases to exist and is replaced by a risk-reducing effect for credit, capital and total risk becoming apparent in the interaction terms ($FIN * PHD$). This effect even overcompensates the risk-increasing effect resulting in a risk-reducing total effect for all three risk measures. This finding supports hypothesis H5c indicating that Ph.D. holders overthink their risk-preferences when losing their position is a potential threat. The results for occupational concentration are not as clear as the results for Ph.D. share. Regarding credit risk occupational concentration has a risk-increasing effect indicating that the free rider problem was an issue during the period before the implementation of FinVAG, which supports Hypothesis H6b. This finding holds true regarding the total risk measure (ZS in column 4). However, focusing on liquidity risk occupational concentration has a positive influence on liquidity and therefore a risk-reducing effect. Concerning the period after the implementation of FinVAG the same risk-reduction ensues for credit risk and total risk which also overcompensates the risk-increasing effect. For liquidity risk the interaction effect is risk-increasing and does overcompensate the aforementioned risk-reducing effect. These findings partially support hypothesis H6c. Another interesting finding is that, although total bank risk (measures as the equity ratio CAP) and Z-score are not influenced by occupational concentration in pre-FinVAG period, a risk reducing effect is measurable in the post-FinVAG period for both variables. Regarding supervisory board power, total bank risk, liquidity risk and Z-Score are influenced in a risk-reducing way for liquidity risk and a risk-increasing effect for total bank risk and Z-Score. This finding indicates that communication problems may be an issue when it comes to the decision-making process related to total bank risk and Z-Score. For liquidity this might not be the case as the concept of liquidity is more accessible. For the period after the implementation of FinVAG the aforementioned effects are weaken but not overcompensated.

Apart from these results some interesting findings in relation to the control variables and risk measure are found. The positive effect of equity on credit risk argues that banks with low equity reduce their credit risk exposure. This finding is consistent with Reeg and Stralla (2016). A shift to more non-interest income increases credit risk exposure. A result which may be attributable to a shift in focus and a lower credit portfolio diversification. The size of a bank seems to positively influence the overall stability as total assets positively influences both equity ratio and Z-Score. Contrary, banks with a greater focus on non-interest income tend to have a lower equity ratio and Z-Score.

Table 4.11

Regression results for the relationship between board characteristics and risk measures (more aggregated occupational groups)

VARIABLES	(1) LLP	(2) CAP	(3) LIQ	(4) ZS
L.LLP	0.089**			
	(0.043)			
L.CAP		1.069***		
		(0.040)		
L.LIQ			0.596***	
			(0.155)	
L.ZS				0.996***
				(0.011)
PHD	0.052**	-0.069*	-0.000	-0.197**
	(0.023)	(0.040)	(0.143)	(0.098)
CON_a	0.018*	-0.020	1.238**	-0.462
	(0.009)	(0.020)	(0.561)	(0.308)
SBP	0.000	-0.001	0.030**	-0.054***
	(0.000)	(0.000)	(0.015)	(0.017)
FIN*PHD	-0.056**	0.091**	0.140	0.207**
	(0.023)	(0.040)	(0.115)	(0.099)
FIN*CON_a	-0.021**	0.033	-1.230**	0.631*
	(0.009)	(0.021)	(0.567)	(0.331)
FIN*SBP	-0.001	0.001	-0.028*	0.048**
	(0.000)	(0.001)	(0.016)	(0.021)
FIN	-0.017*	0.015	0.663**	-0.084
	(0.009)	(0.012)	(0.289)	(0.212)
CAP	0.061*		0.660	0.663
	(0.033)		(0.632)	(0.716)
TA	0.001	0.002*	-0.037	0.050**
	(0.001)	(0.001)	(0.023)	(0.025)
ID	0.019***	-0.022*	-0.071	-0.217*
	(0.003)	(0.013)	(0.234)	(0.116)
ΔGDP	-0.018**	0.041***	-0.058	0.212
	(0.007)	(0.009)	(0.205)	(0.152)
INTRATE	-0.971***	1.044***	7.150	8.444*
	(0.231)	(0.276)	(6.879)	(4.406)
UNEMP	-0.061**	0.197***	-0.126	2.222***
	(0.029)	(0.047)	(1.211)	(0.704)
Constant	0.017	-0.082***	-0.008	-1.126*
	(0.021)	(0.028)	(0.598)	(0.638)
Wald Chi2	113.79***	1,723.51***	307.01***	23,985.61***
AB test AR(1)	-5.95***	-3.89***	-4.02***	-5.67***
AB test AR(2)	0.99	1.50	1.52	0.48
Hansen test, 2nd step	70.73	36.81	22.27	73.67
No. of Instruments	78	49	46	78
No. of Groups	246	246	246	246
No. of Observations	1,230	1,230	1,230	1,230

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results remain mainly the same when a more aggregated measure for occupational diversification is applied (see table 4.11) as a robustness test. The only exceptions are the coefficients in regard to the effects on the equity-ratio which are overall less significant.

Table 4.12

Regression results for the relationship between board characteristics and risk measures (broader equity)

VARIABLES	(1) LLP	(2) CAP_a	(3) LIQ	(4) ZS
L.LLP	0.101**			
	(0.043)			
L.CAP_a		0.925***		
		(0.048)		
L.LIQ			0.497***	
			(0.169)	
L.ZS				0.989***
				(0.010)
PHD	0.047**	-0.081**	-0.123	-0.163*
	(0.021)	(0.039)	(0.143)	(0.091)
CON	0.019*	-0.034	0.856**	-0.506
	(0.010)	(0.029)	(0.432)	(0.315)
SBP	0.000	-0.001	0.020	-0.050***
	(0.000)	(0.001)	(0.013)	(0.015)
FIN*PHD	-0.048**	0.097**	0.250**	0.147*
	(0.021)	(0.040)	(0.108)	(0.084)
FIN*CON	-0.022**	0.038	-0.894**	0.626**
	(0.010)	(0.030)	(0.426)	(0.311)
FIN*SBP	-0.001	0.001	-0.020	0.044**
	(0.000)	(0.001)	(0.012)	(0.018)
FIN	-0.019**	0.015	0.582**	-0.073
	(0.009)	(0.016)	(0.239)	(0.194)
CAP_a	0.066*		-0.219	0.704
	(0.037)		(0.819)	(0.815)
TA	0.001	0.000	-0.042*	0.045**
	(0.001)	(0.001)	(0.025)	(0.022)
ID	0.018***	-0.017	-0.160	-0.245*
	(0.003)	(0.013)	(0.284)	(0.142)
ΔGDP	-0.021***	0.045***	0.047	0.203
	(0.007)	(0.010)	(0.223)	(0.164)
INTRATE	-1.030***	1.053***	10.335	7.671*
	(0.232)	(0.305)	(7.620)	(4.634)
UNEMP	-0.063**	0.149***	0.667	2.308***
	(0.029)	(0.053)	(1.304)	(0.715)
Constant	0.018	-0.034	0.202	-0.986*
	(0.021)	(0.027)	(0.592)	(0.569)
Wald Chi2	125.33***	1,001.43***	330.30***	17,956.39***
AB test AR(1)	-6.04***	-4.29***	-3.58***	-5.65***
AB test AR(2)	1.13	1.62	1.05	0.27
Hansen test, 2nd step	66.02	40.57	24.16	71.79
No. of Instruments	78	49	46	75
No. of Groups	246	246	246	246
No. of Observations	1,230	1,230	1,230	1,230

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.12 summarizes the results of a second robustness test in which a broader measure for the equity ratio is applied. In accordance with the first robustness test the results remain the same to a great extent. Changes are that this broader measure is not significantly influenced by total assets and the income diversification (see column (2)). In addition, regarding the effects on liquidity risk, the effect of supervisory board power ceases to exist. However, Ph.D. holders now unfold a risk-reducing effect after the implementation of FinVAG. Also the liquidity ratio is now negatively influenced by total assets. This result is plausible as bigger banks have less volatility regarding their liquidity needs.

4.7 Conclusion

In this study various methods are applied in order to evaluate the influence of the implementation of FinVAG on German cooperative banks. Therefore, the study focuses on two different supervisory board related issues. First, the identification of structural changes which might be initiated by the implementation of FinVAG. Results show that cooperative banks lose their distinct board structure which relies on farmers heavily due to the historical background of cooperative banks. In addition, it becomes apparent that economic knowledge becomes more important, hence the share of entrepreneurs rises. The second part of the study discusses issues related to the relationship between board characteristics and various risk measures which are explicitly targeted in FinVAG. Therefore, four different risk measures are investigated, namely credit risk, capital risk, liquidity risk and total bank risk. The chosen board characteristics are all competence-related as the FinVAG tries to ensure the expertise of supervisory board members. As a result, the study focuses on the share of Ph.D. holders and occupational background concentration. The results show that the implementation of FinVAG influenced banks and their supervisors in the intended way to a great extent. During the period before the implementation of FinVAG results are in line with previous literature as Ph.D. holders increase the exposure to risk regardless of risk-type. After the implementation of FinVAG this relationship turns into the opposite with lower risk exposure as a result. Regarding occupational concentration and supervisory board power the results are less universal. Both board characteristics are related with lower liquidity risk exposure in pre-FinVAG period and higher exposure in post-FinVAG period. These results also remain consistent profoundly when broader equity and occupational background definitions are applied.

The study provides evidence that regulation of supervisory boards, in the way the FinVAG was realized, may unfold wanted and probably unwanted effects. Results indicate that the intended reduction of risk exposure and the increase in financial stability was realized. On the other hand, results also show that the special, historical grown board structure, with farmer playing an important role, changes to a more common structure in banking. Therefore, the representation and control on behalf of member of cooperative banks may decline. These potentially unwanted effects should also be considered when it comes to regulation.

Appendix 4.A

Variables	Symbol	Description
Definition of variables		
Risk Measures		
Loan Loss Provision	LLP	Loan loss provision over the total gross value of total bank loans
Liquidity Risk	LIQ	Calculated as: (cash assets reserves + overnight debt due + trading assets + inventory on hands + money held in trust)/(total demand deposits)
Equity-to-asset ratio	CAP	Total equity divided by total assets
Alternativ Equity-to-asset ratio	CAP_a	Total equity plus capital with equity properties divided by total assets
Z-Score	ZS	Calculated as: Ln[(Return on Assets + Capital Assets Ration)/(Standard deviation of Return on Assets)]
Board Characteristics		
Share of Ph.D.	PHD	Number of Supervisory Board members possessing a Ph.D. over the total number of Supervisory Board members
Occupational Concentration	CON	Herfindahl index of Supervisory Board member occupations
Alternative Occupational Concentration	CON_a	Herfindahl index of Supervisory Board member occupations (more aggregated occupational groups)
Supervisory Board Power	SBP	Total number of Supervisory Board members over the total number of Executive Board members
FinVAG	FIN	Dummy variable which is 1 in years 2009, 2010 and 2011
Board Structure Variables		
Total number of supervisory board members	TOTAL	The number of supervisory board members
Change in supervisory board	CHANGE	Dummy variable, which is 1 in years in which changes in supervisory board structure or number of supervisory board members occurred.
Female	FEMALE	Number of female supervisory board members.
Control Variables		
Total Assets	TA	Natural logarithm of the sum of all Assets
Income Diversification	ID	Non-interest income over non-interest income and interest income
Change in GDP	ΔGDP	Measures as the percentage difference in German GDP between t-1 and t
Interest rate	INTRATE	Average ECB interest rate, calculated as daily weighted values for each year.
Unemployment rate	UNEMP	Unemployment rate (in %) in Germany (ILO)

Appendix 4.B

Occupational groups in detail (CON) and aggregated (CON_a)

Occupational group (detail)	Occupational group (aggregated)
Tax advisors Auditors	TAXA
Employees Public employees	EMP
Clerks	CLERK
Entrepreneurs	ENT
Lawyers Notaries Judges Judicial Officers	LAW
Doctors Pharmacists Veterinarians	MED
Engineers Computer scientists Architects	ENGI
Farmers and winemakers	FARM
Professors	PROF
Political office	POL
Other Innkeepers Experts Drivers Housemaker Driving school instructors Craftsmen Self-employed craftsmen Mathematicians Pensioners	OTH

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