Empirical Studies of Contemporaneous Banking Research

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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 09. August 2016

Zusammenfassung

Banken nehmen wichtige Funktionen innerhalb einer Volkswirtschaft wahr. Innerhalb ihrer Rolle als Finanzintermediär stellen sie Liquidität bereit und übernehmen elementare Aufgaben der Fristen- und Risikotransformation (Fama ,1985). Sie stellen sicher, dass die Liquidität der Depotinhaber den profitabelsten Investitionsprojekten zukommt. Darüber hinaus übernehmen Banken wichtige Prüfungs- und Überwachungsfunktionen über ihre Investitionsprojekte und sorgen damit für eine stetig effiziente Ressourcenallokation innerhalb einer Volkswirtschaft (Pathan and Faff, 2013).

Da jedoch Banken ihre Finanzdienstleistungen der gesamten Volkswirtschaft zur Verfügung stellen, erzeugen sie damit auch (im Gegensatz zu Firmen) ein gewisses Systemrisiko: die Finanzkrise 2007 – 2008 hat gezeigt, dass Banken ganze Staaten in eine Rezession ziehen können. Gleichzeitig hat die Krise allerdings auch gezeigt, dass bestimmte Banktypen deutlich stabiler sind als andere. So sind beispielsweise die genossenschaftlichen Volks- und Raiffeisenbanken deutlich besser durch die Krise gekommen als nahezu alle Universalbanken. Mögliche Erklärungen für die vergleichsweise gute Performance der Genossenschaftsbanken in der Krise lassen sich bereits aus deren Besonderheiten im Geschäftsmodell ableiten: Genossenschaftsbanken haben einen starken Fokus auf dem Kreditgeschäft und nutzen hierfür ihre Nähe zum Kunden. Darüber hinaus vertreiben sie klar strukturierte Produkte welche die Ansprüche des § 1 GenG erfüllen. Der Zusammenbruch des amerikanischen Häusermarktes hat die Genossenschaftsbanken daher hauptsächlich indirekt durch den makroökonomischen Einbruch getroffen. Aus diesem Grund kamen die Genossenschaftsbanken vergleichsweise gut durch die Krise.

Da sich das Geschäftsmodell der Genossenschaftsbanken demzufolge als sehr stabil erwiesen hat, ist es zum Teil verwunderlich, dass die Forschung hinsichtlich dieses Banktypen deutlich unterrepräsentiert ist. Genossenschaftsbanken existieren in allen größeren westlichen Volkswirtschaften und nehmen innerhalb dieser oft eine bedeutende

Rolle ein. Aufgrund der einerseits hohen Bedeutung von Genossenschaftsbanken in den genannten Volkswirtschaften und der andererseits vergleichsweise geringen Beachtung in der Literatur, ist es das Ziel dieser Dissertation mit den folgenden drei empirischen Studien die bestehende Forschung der Genossenschaftsbanken voranzutreiben. Die drei empirischen Studien beschäftigen sich mit jeweils unabhängigen Forschungsfragen, die für den Bankensektor in jüngster Zeit von hoher Relevanz sind.

Kapitel 2 beschäftigt sich mit der Frage, welche Genossenschaftsbanken von einer Einnahmendiversifikation profitieren können: bestehende Literatur offenbart den Trend innerhalb des Bankensektors, wonach Banken nach Diversifikation streben, indem sie ihre Einnahmen immer stärker im zinsunabhängigen Geschäft generieren. Jedoch zeigt sich in der Literatur ebenfalls, dass längst nicht alle Banken durch die Einnahmendiversifikation profitieren (Mercieca et al., 2007; Stiroh and Rumble, 2006; Goddard et al., 2008). Stiroh und Rumble (2006) belegen in ihrer Studie, dass die Performance von großen amerikanischen Universalbanken (US Financial Holding Companies) durch den stärkeren Fokus auf dem zinsunabhängigen Geschäft zurückgeht. Die Autoren sind der Ansicht, dass derartige Großbanken das Diversifikationspotenzial überschätzt haben. Die Einnahmen von Genossenschaftsbanken hingegen unterscheiden sich mitunter deutlich von denen der Universalbanken: Universalbanken handeln Aktien, Derivate, Zertifikate und andere Finanzinstrumente. Hinsichtlich des Kreditgeschäfts fokussieren sie sich meist auf mittelgroße bis große Unternehmen. Genossenschaftsbanken hingegen generieren ihr zinsunabhängiges Geschäft zum großen Teil durch Provisionen und bestimmte Service-Gebühren. Den Großteil der Zinserträge erzielen sie durch das Kreditgeschäft. Ihre Kunden im Kreditgeschäft sind meist kleine bis mittelständige Unternehmen sowie Privatkunden aus der Region. Die Unterschiede auf der Einnahmenseite könnten bedeuten, dass die Ergebnisse aus der Studie von Stiroh und Rumble (2006) nicht auf die Genossenschaftsbanken übertragbar sind. Demnach ist es das Ziel dieses Kapitels, zu untersuchen, welche der deutschen Genossenschaftsbanken über den Zeitraum 2005 bis 2010 von einer Einnahmendiversifikation profitieren können.

Die Ergebnisse der empirischen Untersuchung bestätigen die Vermutung, dass die Erkenntnisse aus der Studie von Stiroh und Rumble (2006) nicht auf Genossenschaftsbanken zu übertragen sind. Es stellen sich die folgenden zwei Effekte ein: eine Einnahmenkonzentration wirkt sich positiv auf die risikoadjustierte Rendite von Genossenschaftsbanken aus (indirekter Effekt). Gleichzeitig zeigt sich, dass das zinsunabhängige Geschäft profitabler ist als das Zinsgeschäft (direkter Effekt). Die daraufhin folgende Auswertung, nach dem zugrundeliegenden Anteil vom zinsunabhängigen Geschäft, ergibt folgendes Bild: es profitieren diejenigen Banken von einer weiteren Einnahmendiversifikation, welche bereits einen hohen Anteil ihrer Einnahmen durch das zinsunabhängige Geschäft generieren. Dies ergibt sich daraus, dass für diese Banken der positive direkte Effekt den negativen indirekten Effekt überkompensiert und in der Konsequenz zu einem positiven Nettoeffekt führt. Des Weiteren zeigt die Untersuchung einen negativen Nettoeffekt für diejenigen Banken, welche den Großteil ihrer Einnahmen durch das Zinsgeschäft generieren. Demzufolge bedeutet das für diese Banken, dass eine weitere Einnahmendiversifikation (durch einen stärkeren Fokus auf das zinsunabhängige Geschäft) zu niedrigeren risikoadjustierten Erträgen führt. Demnach sollten sich diese Banken weiterhin auf ihr Kerngeschäft, also das Zinsgeschäft, konzentrieren. Insgesamt deuten die Hinweise der empirischen Untersuchung darauf hin, dass Banken eine gewisse Zeit benötigen um entsprechende Expertise und Erfahrung aufzubauen damit eine Einnahmendiversifikation eine konkurrenzfähige risikoadjustierte Rendite erzeugt.

Kapitel 3 beschäftigt sich mit der Beziehung zwischen dem Risiko, der Kapitalausstattung und der Effizienz einer Bank: die technologische Entwicklung, die Deregulierung und die Einführung des Euro als Gemeinschaftswährung haben den Wettbewerb auf dem Europäischen Bankenmarkt in den letzten 20 Jahren deutlich verschärft. Um Wettbewerbsfähig zu bleiben sahen sich die Banken gezwungen ihre Effizienz zu erhöhen. Demzufolge versuchten Banken näher an der „best practice“ Produktionsfunktion - im Sinne der Input – Output Relation - zu operieren. Die zentrale Frage die sich dabei stellt ist, ob Banken ihre Effizienz auf Kosten eines höheren Risikos erkauften, um entgehende

Erträge zu kompensieren. Im Zusammenhang mit dem Bankrisiko beschäftigt sich ein Großteil der Literatur mit Problemkrediten. Einige dieser Studien belegen, dass Banken große Anteile an Problemkrediten im Portfolio aufweisen ehe sie Insolvenz anmelden (Barr und Siems ,1994; Demirgüc-Kunt, 1989). Hinsichtlich der Bankeffizienz zeigen weitere Studien, dass die durchschnittliche Bank eine niedrige Profitabilität bei gleichzeitig hoher Kostenposition im Vergleich zur „best practice“ Produktionsfunktion aufweist (Fiordelisi et al., 2011; Williams, 2004). Auf den ersten Blick scheinen diese beiden Forschungsstränge keine Gemeinsamkeit aufzuweisen. Jedoch zeigen Berger und DeYoung (1997), dass Banken mit einem unfähigen Management weder fähig sind die Kostenseite zu optimieren (niedrige Kosteneffizienz) noch in der Lage sind ihre Kreditnehmer und damit die Kreditqualität (hohes Kreditrisiko) in angemessener Weise zu überwachen. In der Konsequenz führt die negative Beziehung zwischen Kosteneffizienz und notleidenden Krediten zu einer niedrigeren Eigenkapitalausstattung. Darüber hinaus zeigen unter anderem Williams (2004) und Berger und DeYoung (1997), dass Banken mit niedrigem Eigenkapital tendenziell zu einem moralischen Risikoverhalten („moral hazard“) neigen, welches letztendlich zur Insolvenz führen kann.

Das Geschäftsmodell von Genossenschaftsbanken beruht auf der Förderung der Interessen der Mitglieder (§ 1 GenG). Das legt die Vermutung nahe, dass die in der Literatur weit verbreitete Ansicht des moralischen Risikoverhaltens nicht auf Genossenschaftsbanken zutrifft. Darüber hinaus könnten die besonderen Governance-Strukturen von Genossenschaftsbanken diese These stützen: kurzfristige Eigentümerinteressen als mögliche Ursache für moralisches Risikoverhalten spielen bei Genossenschaftsbanken keine Rolle. Neben diesem Zusammenhang zeigt sich, dass die Liquidität von Banken in diesem Forschungsfeld keine große Beachtung findet. Die gängige Auffassung in der Literatur ist, dass die Liquidität einer Bank kein Problem darstellt, da Zugang zu zusätzlichen liquiden Mitteln relativ einfach zu erhalten ist. Jedoch hat die letzte Finanzkrise 2007 – 2008 offenbart, dass sich Banken, aufgrund des zu dieser Zeit hohen Misstrauens innerhalb der Branche, Liquiditätsengpässen gegenüber gesehen haben. Aus diesem Grund untersucht

dieses Kapitel mittels Daten von deutschen Genossenschaftsbanken von 2005 bis 2010 zum einen, ob diese Banken das in der Literatur beobachtete moralische Risikoverhalten aufweisen. Zum anderen wird untersucht, wie sich das Liquiditätsrisiko auf die Effizienz und die Eigenkapitalposition einer Bank auswirkt.

Die Ergebnisse der empirischen Untersuchung bestätigen größtenteils die in der Literatur beobachteten Zusammenhänge. Die Ergebnisse zeigen, dass eine niedrigere Kosten- und Gewinneffizienz zu einem höheren Kreditrisiko führt. Gleichzeitig bestätigen die Ergebnisse, dass ein negativer Zusammenhang zwischen dem Kreditrisiko von Banken und deren Kosten- und Gewinneffizienz besteht. Als zentraler Unterschied zu bestehenden Studien zeigt sich jedoch, dass ein positiver Zusammenhang zwischen der Eigenkapitalposition und dem Kreditrisiko besteht. Das bedeutet, dass moralisches Risikoverhalten („moral hazard“) bei Genossenschaftsbanken, wie bereits vermutet, nicht stattfindet. Insbesondere der Zweck der Genossenschaftsbanken (§ 1 GenG) und die damit einhergehenden besonderen Governance-Strukturen sind nach Ansicht der Autoren die wesentliche Begründung für diese Erkenntnis. Weitere Ergebnisse weisen entgegen der Studie von Fiordelisi et al. (2011) darauf hin, dass die Eigenkapitalposition und die Kosteneffizienz einer Bank in einer negativen Beziehung zueinander stehen. Dies bedeutet, dass Genossenschaftsbanken mit einer schlechten Performance in künftigen Perioden insbesondere darauf achten ihre Kostenposition zu optimieren. Zuletzt können die Autoren – hinsichtlich der Liquidität von Banken – entsprechende Risikopräferenzen des Bankmanagements nachweisen. So zeigt sich, dass Banken mit einer hohen Liquidität weniger am Aktienmarkt investiert sind und eine höhere Eigenkapitalausstattung aufweisen.

Kapitel 4 widmet sich den Governance-Strukturen von Genossenschaftsbanken: Die Finanzkrise 2007 - 2008 hat zu enormen Verwerfungen auf dem Bankenmarkt geführt. Die Pleite der Investmentbank Lehman Brothers war der Anfang von zahlreichen Regierungs-interventionen in weiten Teilen der Welt, um die heimische Volkswirtschaft vor noch größeren Schäden zu schützen. Im Nachgang der Krise machten Politiker und Regulatoren Governance-Schwächen als eine der wesentlichen Ursachen der Krise aus. Neben

zahlreichen Studien in der Literatur (e.g. Beltratti and Stulz, 2012; Diamond and Rajan, 2009; Erkens et al., 2012) stützt auch eine OECD Studie von 2009 diese These (Kirckpatrick, 2009). In der Folgezeit führten öffentliche Diskussionen zu einem höheren Bewusstsein für geeignete Governance-Mechanismen. Als Konsequenz forderten führende Politiker und Regulatoren mehr finanzielle Expertise in den Aufsichtsräten der Banken. Demzufolge führt das Basel Komitee der Bankenaufsicht in der Richtlinie 2 an: „board members should remain qualified, individually and collectively, for their positions. They should understand their oversight and corporate governance role and be able to exercise sound, objective judgement about the affairs of the bank." (BCBS, 2015). Unter Berücksichtigung dieser Auffassung stellt sich allerdings die Frage, ob finanzielle Expertise in den Aufsichtsräten von Banken tatsächlich eine größere Stabilität gewährleisten?

Dieses Kapitel beschäftigt sich mit dieser Frage unter Bezugnahme auf die Studie von Minton et al. (2014). In ihrer Studie untersuchen die Autoren Amerikanische Commercial Bank Holding Companies (BHCs) im Zeitraum 2003 bis 2008. Die Autoren zeigen, dass Finanzexperten in den Aufsichtsräten von amerikanischen BHCs eine prozyklische Bankperformance fördern. Das bedeutet, dass die Autoren nachweisen, dass die Finanzexperten zwar eine höhere Bankperformance im Vorkrisenzeitraum (2003 bis 2006) erzeugen konnten, darüber hinaus allerdings im Krisenzeitraum (2007 – 2008) zu einer umso schlechteren Bankperformance beigetragen haben. Demnach stellen die Autoren die Ansicht der Politiker und Regulatoren, dass zusätzliche Finanzexperten in den Aufsichtsräten von Banken zu einer höheren Bankstabilität führen, infrage.

Jedoch können Minton et al. (2014) nicht identifizieren, durch welche Ursache ihre Ergebnisse zu erklären sind: Zum einen könnten Finanzexperten, welche im (kurzfristigen) Renditeinteresse der Eigner handelten die prozyklische Bankperformance verursacht haben. Andererseits könnte die höhere Risikobereitschaft der Finanzexperten (aufgrund eines tieferen Verständnisses von Finanzinstrumenten) die Ursache sein.

Genau an dieser Stelle knüpft dieses Kapitel an: Würde sich beispielsweise bei der Untersuchung von deutschen Genossenschaftsbanken das gleiche Ergebnis, also das Finanzexperten eine prozyklische Bankperformance erzeugen, einstellen, so wäre die Ursache hierfür eindeutig: da kurzfristige Renditeinteressen der Eigentümer bei Genossenschaftsbanken keine Rolle spielen wäre eine prozyklische Bankperformance lediglich auf die höhere Risikobereitschaft der Finanzexperten zurückzuführen.

Die Ergebnisse zeigen, dass Finanzexperten in den Aufsichtsräten von Genossenschaftsbanken im Zeitraum von 2006 bis 2011 keine prozyklische Bankperformance erzeugen. Im Gegenteil, die Ergebnisse weisen darauf hin, dass Finanzexperten in den Aufsichtsräten von Genossenschaftsbanken eine langfristige Stabilität der Banken gewährleisten. In der Konsequenz bedeutet das, dass Regulatoren die Eigentümerstrukturen (und damit das Geschäftsmodell) von Banken berücksichtigen sollten, wenn sie neue regulatorische Anforderungen hinsichtlich Finanzexperten in den Aufsichtsräten von Banken einführen.

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1 Introduction and Summary

Banks perform important functions for the economy. Besides financial intermediation, banks provide information, liquidity, maturity- and risk-transformation (Fama, 1985). Banks ensure the transfer of liquidity from depositors to the most profitable investment projects. In addition, they perform important screening and monitoring services over investments hence contributing steadily to the efficient allocation of resources across the economy (Pathan and Faff, 2013). Since banks provide financial services all across the economy, this exposes banks (as opposed to non-banks) to systemic risk: the recent financial crisis revealed that banks can push economies into severe recessions. However, the crisis also revealed that certain bank types appear far more stable than others. For instance, cooperative banks performed better during the crisis than commercial banks. Different business models may reason these performance-differences: cooperative banks focus on relationship lending across their region, hence these banks suffered less from the collapse of the US housing market.

Since cooperative banks performed better during the crisis than commercial banks, it is quite surprising that research concerning cooperative banks is highly underrepresented in the literature. For this reason, the following three studies aim to contribute to current literature by examining three independent contemporaneous research questions in the context of cooperative banks.

The initial data for the three studies exhibits 354 cooperative banks from Bavaria from 2005 to 2011. As such, the dataset used is not a random sample from German cooperative banks but a systematic sample. Table 1.1 and 1.2 show the differences in size and business model from cooperative banks in Bavaria compared to other cooperative banks in Germany.[1]

[1] Source: Bundesverband der Deutschen Volksbanken und Raiffeisenbanken, regionale Statistik, pp. 116 – 123.

Table 1.1 Distribution of cooperative banks in Germany by size ranges (accumulated total assets) and region as of 2010.

	Total Assets < 50 Mil. Euro	Total Assets 50 < 100 Mil. Euro	Total Assets 100 < 250 Mil. Euro	Total Assets 250 < 500 Mil. Euro	Total Assets 500 Mil. < 1 Bil. Euro	Total Assets 1 < 5 Bil. Euro	Total Assets 5 < Bil. Euro	Total
Baden-Württemb.	616	2.386	9.048	14.860	29.389	62.468	7.304	126.071
Bavaria	601	2.816	15.411	27.031	38.128	39.644	0	123.631
FFM/Nord-deutschland	873	2.105	13.996	32.190	40.801	58.838	27.656	176.458
Rheinland/ Westfalen	313	1.893	9.503	12.511	28.436	72.902	45.183	170.741
Weser-Ems	77	140	3.917	5.293	5.648	3.474	0	18.550
Total	2.480	9.340	51.875	91.886	142.402	237.326	80.143	615.451

Table 1.2 Number of branches, number of members, loans to customers and deposits from customers in Germany by regions as of 2010.

	Branches	Members	Loans to Customers (in Mil. Euro)	Deposits from Customers (in Mil. Euro)
Baden-Württemb.	2.895	3.354.473	69.657	90.453
Bavaria	2.799	2.416.352	67.986	93.943
FFM/Nord-deutschland	3.819	3.942.944	101.131	131.035
Rheinland/ Westfalen	1.929	2.635.583	100.476	111.200
Weser-Ems	375	455.744	13.143	12.162
Total	11.817	12.805.096	352.393	506.692

Table 1.1 shows that the region Weser-Ems exhibits the least total asset exposure of the regions, whereas FFM/Norddeutschland exhibits the highest total asset exposure. The total asset exposure of cooperative banks in Bavaria equals 123.631 Billion Euro and hence lies between the aforementioned regions. The distribution of cooperative banks in Bavaria by size does not differ substantially from other regions of Germany.[2] In terms of the business model, Table 1.2 shows differences in the number of branches, number of members, loans to customers and deposits from customers across regions. The region of Weser-Ems exhibits the lowest amount of branches and customers, which is according to Table 1.1 quite reasonable. Similar to Table 1.1., the region FFM/Norddeutschland appears to exhibit the most branches and members. Bavarian cooperative banks exhibit 2.799 branches and 2.416.352 members and hence lie between the aforementioned regions. Most importantly, the loan to deposit ratio seems to be relatively similar across regions.[3] As the numbers in Table 1.1 and 1.2 indicate, cooperative banks from Bavaria can be considered as representative for cooperative banks in Germany. The details about the final sample used in each study are provided within the respective chapter.

Chapter 2 examines whether cooperative banks benefit from revenue diversification: Current banking literature reveals the recent trend in the overall banking industry that banks may opt for diversification by shifting their revenues to non-interest income. However, existing literature also shows that not every bank benefits from revenue diversification (Mercieca et al., 2007; Stiroh and Rumble, 2006; Goddard et al., 2008). Stiroh and Rumble (2006) find that large commercial banks (US Financial Holding Companies) perceive decreasing performance by shifting revenues towards non-interest income. Revenues from cooperative banks differ from those of commercial banks: commercial banks trade securities and derivatives, sell investment certificates and other trading assets. Concerning the lending

[2] Baden-Württemberg exhibits 1 bank, FFM / Norddeutschland exhibits 4 banks and Rheinland / Westfalen exhibits 2 banks larger than 5 Bil. Euro of total assets.
[3] Source: Bundesverband der Deutschen Volksbanken und Raiffeisenbanken, regionale Statistik, pp. 116 – 123.

business, commercial banks focus on providing loans for medium-sized and large companies rather than for small (private) customers. Cooperative banks rely on commission income (fees) from monetary transactions and selling insurances as a source of non-interest income. They generate most of their interest income by providing loans to small and medium-sized companies as well as to private customers in the region. These differences in revenues raise the question whether findings from Stiroh and Rumble (2006) apply to cooperative banks. For this reason, Chapter 2 evaluates a sample of German cooperative banks over the period 2005 to 2010 and aims to investigate the following research question: which cooperative banks benefit from revenue diversification?

Results show that findings from Stiroh and Rumble (2006) do not apply to cooperative banks. Revenue concentration is positive related to risk-adjusted returns (indirect effect) for cooperative banks. At the same time, non-interest income is more profitable than interest income (direct effect). The evaluation of the underlying non-interest income share shows that banks who heavily focus on non-interest income benefit by shifting towards non-interest income. This finding arises due to the fact, that the positive direct effect dominates the negative indirect effect, leading in a positive (and significant) net effect. Furthermore, results reveal a negative net effect for banks who are heavily exposed to interest generating activities. This indicates that shifting to non-interest income decreases risk-adjusted returns for these banks. Consequently, these banks do better by focusing on the interest business. Overall, results show evidence that banks need time to build capabilities, expertise and experience before trading off return and risk efficiently with regard on revenue diversification.

Chapter 3 deals with the relation between credit risk, liquidity risk, capital risk and bank efficiency: There has been rising competition in the European banking market due to technological development, deregulation and the introduction of the Euro as a common currency in recent decades. In order to remain competitive banks were forced to improve efficiency. That is, banks try to operate closer to a “best practice” production function in the sense that banks improve the input – output relation. The key question in this context is if

banks improve efficiency at a cost of higher risk to compensate decreasing earnings. When it comes to bank 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 (Barr and Siems, 1994; Demirgüc-Kunt, 1989). According to efficiency, studies show that the average bank generates low profits and incorporates high costs compared to the "best practice" production frontier (Fiordelisi et al., 2011; Williams, 2004). At first glance, these two issues do not seem related. However, Berger and DeYoung (1997) show that banks with poor management are less able to handle their costs (low cost-efficiency) as well as to monitor their debtors in an appropriate manner to ensure loan quality. The negative relationship between cost efficiency and non-performing loans leads to declining capital. Existing studies (e.g. Williams, 2004; Berger and DeYoung, 1997) show that banks with a low level of capital tend to engage in moral hazard behavior, which in turn can push these banks into bankruptcy.

However, the business model of cooperative banks is based on the interests of its commonly local customers (the cooperative act: § 1 GenG). This may imply that the common perception of banks engaging in moral hazard behavior may not apply to cooperative banks. Since short-term shareholder interests (as a potential factor for moral hazard behavior) play no role for cooperative banks this may support this notion. Furthermore, liquidity has been widely neglected in the existing literature, since the common perception has been that access to additional liquid funds is not an issue. However, the recent financial crisis revealed that liquidity dried up for many banks due to increased mistrust in the banking sector. Besides investigating moral hazard behavior, using data from 2005 to 2010 this study moves beyond current literature by employing a measure for liquidity risk in order to evaluate how liquidity risk relates to efficiency and capital.

Results mostly apply to current literature in this field since the empirical evaluation reveals that lower cost and profit-efficiency Granger-cause increases in credit risk. At the same time, results indicate that credit risk negatively Granger-causes cost and profit-efficiency, hence revealing a bi-directional relationship between these measures. However,

most importantly, results also show a positive relationship between capital and credit risk, thus displaying that moral hazard behavior does not apply to cooperative banks. Especially the business model of cooperative banks, which is based on the interests of its commonly local customers (the cooperative act: § 1 GenG) may reason this finding. Contrary to Fiordelisi et al. (2011), results also show a negative relationship between capital and cost-efficiency, indicating that struggling cooperative banks focus on managing their cost-exposure in following periods. Concerning the employed liquidity risk measure, the authors find that banks who hold a high level of liquidity are less active in market related investments and hold high shares of equity capital. This outcome clearly reflects risk-preferences from the management of a bank.

Chapter 4 examines governance structures of cooperative banks: The financial crisis of 2007/08 led to huge distortions in the banking market. The failure of Lehman Brothers was the beginning of government interventions in various countries all over the world in order to prevent domestic economies from even further disruptions. In the aftermath of the crisis, politicians and regulators identified governance deficiencies as one major factor that contributed to the crisis. Besides existing studies in the banking literature (e.g. Beltratti and Stulz, 2012; Diamond and Rajan, 2009; Erkens et al., 2012) an OECD study from 2009 supports this notion (Kirkpatrick, 2009). Public debates increased awareness for the need of appropriate governance mechanisms at that time. Consequently, politicians and regulators called for more financial expertise on bank boards. Accordingly, the Basel Committee on Banking Supervision states in principle 2 that "board members should remain qualified, individually and collectively, for their positions. They should understand their oversight and corporate governance role and be able to exercise sound, objective judgement about the affairs of the bank." (BCBS, 2015). Taking these perceptions into consideration the prevailing question is whether financial experts on bank boards do really foster bank stability?

This chapter aims to investigate this question by referring to the study from Minton et al. (2014). In their study, the authors investigate US commercial bank holding companies

between the period 2003 and 2008. The authors find that financial experts on the board of US commercial bank holding companies promote pro-cyclical bank performance. Accordingly, the authors question regulators view of more financial experts on the board leading to more banking stability.

However, Minton et al. (2014) do not examine whether their findings accrue due to financial experts who act in the interests of shareholders or due to the issue that financial experts may have a more risk-taking attitude (due to a better understanding of financial instruments) than other board members.

Supposed that their findings accrue due to financial experts who act in the interests of shareholders. Then financial experts on the board of banks where short-term shareholder interests play no role (cooperative banks) may prove beneficial with regard on bank performance during the crisis as well as in normal times. This would mean that they use their skills and expertise to contribute sustainable growth to the bank. Contrary, if this study reveals pro-cyclical bank performance related to financial experts on the board of cooperative banks, this finding may be addressed solely to the risk-taking attitude of financial experts (since short-term shareholder interests play no role). For this reason, this chapter aims to identify the channel for the relation of financial experts and bank performance by examining the following research question: Do financial experts on the board promote pro-cyclical bank performance in a setting where short-term shareholder interests play no role?

Results show that financial experts on the board of cooperative banks (data from 2006 to 2011) do not promote pro-cyclical bank performance. Contrary, results show evidence that financial experts on the board of cooperative banks appear to foster long-term bank stability. This suggests that regulators should consider ownership structure (and hence business model of banks) when imposing new regulatory constraints for financial experts on the bank board.

2 Which Cooperative Banks benefit from Revenue Diversification?

Abstract

Current banking literature reveals the recent trend in the overall banking industry that banks may opt for diversification by shifting their revenues to non-interest income. Consequently, this paper asks which cooperative banks in Germany are able to increase performance during the period 2005 to 2010 by shifting revenues towards non-interest income. Results show that concentration (indirect effect) is significantly positive related to risk-adjusted returns. At the same time, there is a significant positive impact on risk-adjusted returns for non-interest income (direct effect). The evaluation of the net effect shows that banks who are heavily exposed to non-interest income benefit by shifting towards non-interest income since the direct effects dominates the indirect effect. This may imply that a bank's diversification strategy depends on its business line exposure, which in turn may have implications for managers, supervisors and regulators.

JEL classification: G15, G21, G28

Keywords: Cooperative banks, Revenue diversification, Risk/return performance

2.1 Introduction

Lending business has been the most important business for virtually all banks around the world some decades ago. However, increasing competition in the overall banking industry led to declining interest margins. Additionally, financial market deregulation in recent decades (starting in the early 1990s) motivated banks to seek new business opportunities in order to gain market share and to remain competitive. Thus, non-interest income has become another major revenue stream next to interest income. However, current banking literature reveals that bank managers may have overestimated the opportunity to diversify and hence bank performance may suffer due to this development (Busch and Kick, 2015; DeYoung and Rice, 2004; Esho, Kofman, Sharpe, 2005; Goddard et al., 2008; Laeven and Levine, 2007; Lepetit et al., 2008; Stiroh, 2004a; Stiroh and Rumble, 2006). Stiroh and Rumble (2006) show that commercial banks (US Financial Holding Companies) perceive decreasing performance by shifting revenues towards non-interest income.

This paper empirically examines whether this finding applies to cooperative banks as well. Specifically differences on the revenue side between commercial banks (US Financial Holding Companies) and cooperative banks may yield different outcomes: commercial banks trade securities and derivatives, sell investment certificates and other trading assets. Concerning the lending business, commercial banks focus on providing loans for medium-sized and large companies rather than for small (private) customers. Cooperative banks rely on commission income (fees) from monetary transactions and selling insurances as a source of non-interest income. They generate most of their interest income by providing loans to small and medium-sized companies as well as to private customers in the region.

As the sample of small and medium sized banks used in this study is of cooperative banks from Germany, the paper proceeds by lighting up the German banking sector before further describing the value proposition of this study.

Literature refers the German banking system commonly as the “three-pillar banking system” (Brunner et al., 2004). The three pillars are commercial banks, cooperative banks

and savings banks, which comprise 2.029 financial institutions in Germany as of 2013. There were 1.078 cooperative banks, who account for 13.6% of total assets of the German banking industry in 2013.[4] They offer financial services to 30 Mio. Customers and 17.7 Mio. members in Germany. The overall credit volume reached 462 Billion Euro whereas deposits were achieved over 573 Billion Euro in the same period. Accumulated total assets indicated over 763 Billion Euro in 2013.[5] These numbers indicate that cooperative banks comprise an important part of the German banking industry.

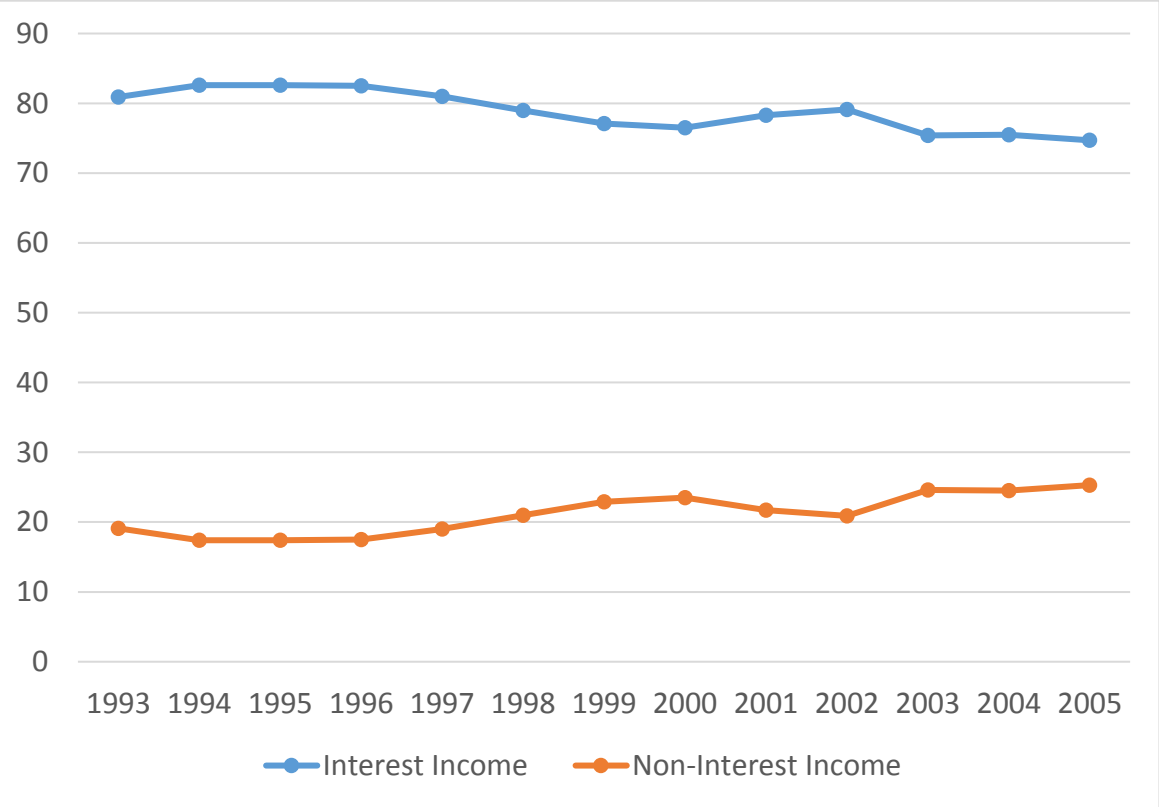
Cooperative and commercial banks differ in their corporate strategy. Profit generation is not the primary objective of cooperative banks as opposed to commercial banks. Cooperative banks aim to meet the needs of their members and provide financial services to the community in their region. Profits remain inside the institution or return to members (Bauer, 2007; Wilcox, 2006; Genossenschaftsverband: Jahresbericht 2013). Their customers are mostly small and medium-sized enterprises and retail customers. Consequently, one can say that these banks operate in a niche market: cooperative banks maintain long-term relationships to their customers by evaluating soft information. Contrary, Commercial banks may face informational cost disadvantages (higher agency costs) as they do not base their business model on evaluating soft information from their customers (Stein, 2002). For this reason, they do not base their business model on relationship lending.

Figure 2.1 shows the development of non-interest income and interest income of the cooperative banking sector in Germany. The figure shows that the share of interest income is decreasing since 1993 while the share of non-interest income is increasing. Thus, the observed trend in the literature also applies to the cooperative banking sector in Germany: these banks show on average that non-interest income comprises a growing part of operating income.

[4] Bankenverband, 2014.
[5] Genossenschaftswesen, 2015.

However, there is large variation within the cooperative banking sector with regard to strategic focus: while some banks generate primarily interest income, others focus on non-interest generating activities. Those who generate primarily interest income are also heterogenic with respect to their focus on real estate lending, municipal lending and consumer lending. Banks who generate primarily non-interest income differ in their focus on commission, trading or other earning activities. Finally, some cooperative banks are more

Figure 2.1 Interest and non-interest income as a percentage of operating income.[6]



profitable than others. These differences raise the following question: which cooperative banks benefit by revenue diversification?

[6] Source: Bundesbank online.

Banks can diversify their revenue streams by shifting interest-generating activities to non-interest generating activities. Moreover, they can diversify within interest generating activities by diversifying their loan portfolio. Similarly, they can diversify within non-interest generating activities by shifting e.g. commission income to trading or other non-interest generating income.

The sample of this study consists of 354 cooperative banks during 2005 to 2010. As these banks are non-listed banks, common accounting based measures (return on equity and return on assets) of bank profits are used. In order to gauge the impact of diversification on risk-adjusted returns and the Z-score the author uses the Herfindahl Hirschman Index[7]. The Z-score indicates how diversification affects a banks insolvency risk: the higher the volatility of returns the higher is a banks insolvency risk (Mercieca et al., 2007).

The results show that concentration is significantly positive related to risk-adjusted returns. This means that cooperative banks do better by focusing on specific business lines (indirect effect). At the same time, the results show that non-interest income increases risk-adjusted returns (direct effect). Since there is a non-linear relationship concerning the net effect, this could mean that the net effect depends on the underlying share of non-interest income. For this reason, the author evaluates the net effect at different values of the average non-interest share for various percentiles, which leads to the following findings: banks who are already heavily exposed to non-interest income benefit by shifting towards non-interest income since the direct effects dominates the indirect effect for these banks. At the same time, banks who focus on interest income should keep sticking to the interest business.

This paper adds to the research in several ways: First, this paper moves beyond familiar studies in this field (Goddard et al., 2008; Mercieca et al., 2007; Stiroh, 2004b) by considering non-linearity in the net effect. Second, Stiroh and Rumble (2006) indeed consider non-linearity in their study of large banks. However, since commercial banks (US Financial

[7] The Herfindahl Hirschman Index is a common measure of diversification in the finance literature. See e.g. Busch and Kick, 2015; DeYoung and Rice, 2004; Esho et al., 2005; Goddard et al., 2008; Hirtle and Stiroh, 2007; Mercieca et al., 2007; Stiroh, 2004b; Stiroh and Rumble (2006) who all use this diversification measure.

Holding Companies) yield completely different revenue streams this could mean that their results do not necessarily apply to cooperative banks. Since cooperative banks fulfill important functions in the banking business in several developed economies, it is important to evaluate strategies that may prove beneficial for these banks.

The paper proceeds as follows: Section 2.2 summarizes current banking literature concerning the impact of diversification on bank performance. Section 2.3 describes the data and provides summary statistics of the sample used in this study. Section 2.4 shows the empirical model and results. The paper ends with a conclusion.

2.2 Literature

A large strand of literature observes an increasing importance of non-interest income in the banking industry since 1990 (Busch and Kick, 2015; DeYoung and Rice, 2004; Esho et al., 2005; Goddard et al., 2008; Laeven and Levine, 2007; Lepetit et al., 2008; Stiroh, 2004a; Stiroh and Rumble, 2006). Most of these studies discuss the observed shift towards non-interest income in the context of diversification (Goddard et al., 2008; Hirtle and Stiroh, 2007; Mercieca et al., 2007; Stiroh 2004b; Stiroh and Rumble, 2006). Growing importance of non-interest income might have several reasons: Next to the reasons mentioned at the beginning (financial deregulation, increased competition) cross-selling strategies may have contributed to this development: banks who rely heavily on relationship lending may use information about their customers to provide additional financial services to them. This might steadily increase the share of non-interest income for these banks. With regard to declining interest margins due to increased competition, this development may have increased returns and diversified risk.

Since cooperative banks primarily focus on relationship lending, they are able to exploit cross-selling strategies. However, there are also risk factors involved as Lepetit et al. (2008) note: First, switching and information costs of traditional banking activities

(relationship lending) are relatively high for both borrowers and lenders. Thus, traditional banking activities are relatively stable as opposed to non-traditional banking activities (non-interest income) who incorporate lower switching costs and hence higher fluctuation. Second, increasing non-interest income raises fixed costs (due to e.g. additional staff) and hence increases operational leverage. In contrast, merely interest expenses determine marginal costs of an existing relationship. Third, banks are required to hold capital for interest generating activities by regulators. As banks do not need to hold capital for non-interest income, banks with a higher share of non-interest income may incorporate higher risk due to higher financial leverage (Demsetz and Strahan, 1997; DeYoung and Roland, 2001; Morgan and Samolyk, 2003).

A Growing share of non-interest income could also mean that interest-generating activities become less important for banks. However, current literature does not show this notion, since several studies reveal growing interest income as well (DeYoung and Rice, 2004; Hirtle and Stiroh, 2007; Stiroh, 2004a). Thus, increasing non-interest income might rather coexist than replace interest income. This finding seems to be in line with the issue that banks use lending business in order to reap benefits of cross selling.

There are several studies which are of particular interest for the author's investigation: these studies measure diversification effects by samples of credit unions (Goddard et al., 2008), community banks (Stiroh, 2004b), other small banks (Mercieca et al., 2007) and US financial holding companies (Stiroh and Rumble, 2006).

Stiroh (2004b) analyzes a sample of US credit unions through the period 1984 to 2000. The study shows that non-interest income decreases risk-adjusted returns. At the same time, results show that concentration increases risk-adjusted returns. As a result, the author identifies a negative net effect for the median community bank. In addition, results show diversification benefits within business lines but not between. However, the empirical analysis does not address non-linearity concerning the net effect.

Similar to the study from Stiroh (2004b), Mercieca et al. (2007) analyze a sample of small European banks (cooperative, savings, commercial, mortgage and credit banks) in terms of diversification benefits. The sample contains 755 small banks during the period 1997-2003. The authors measure a negative but insignificant relation between concentration and risk-adjusted returns. Moreover, they identify that non-interest income negatively relates to bank performance. The net effect is negative and highly significant at the median non-interest share. Similar to Stiroh (2004b) they do not consider non-linearity concerning the net effect. As opposed to the study from Stiroh (2004b) the authors do neither find diversifications benefits within nor between business lines.

The last study that examines small banks in this context is the study from Goddard et al. (2008) who investigate the impact of revenue diversification on financial performance by their sample of US credit unions using data from 1993 to 2004. They identify that concentration increases risk-adjusted returns. As opposed to Stiroh (2004b) and Mercieca et al. (2007) they do (partly) consider non-linearity in the net effect. However, they do merely consider the 5^{th} to the 25^{th} percentile in their evaluation of the net effect. They conclude that small banks should rather focus on traditional activities due to limited capacities and technologies in diversification, as opposed to large banks who should further exploit diversification opportunities.

Stiroh and Rumble (2006) analyze a sample of US financial holding companies (FHCs) during the years 1997 to 2002. To the best of the authors knowledge, this is the only existing study that comprehensively considers non-linearity in the net effect. Consequently, the authors evaluate the net effect for the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentile. They identify three main effects: first, non-interest income decreases risk-adjusted returns. Second, diversification increases risk-adjusted returns (this implicates that concentration negatively relates to risk-adjusted returns). Third, FHCs who are already heavily exposed to non-interest income (75^{th} and 90^{th} percentile) perceive decreasing performance (risk-adjusted returns) in the case that they keep shifting business towards non-interest income. Thus, the authors conclude that FHCs may have overestimated the positive effects of revenue diversification.

Taken together, there are studies that examine diversification effects of small banks. However, these studies do not comprehensively address non-linearity concerning the net effect. Most of the studies merely evaluate the net effect at the 50th percentile (Mercieca et al., 2007; Stiroh, 2004b). Goddard et al. (2008) do partly consider non-linearity in their study. The study from Stiroh and Rumble (2006) is the only one that comprehensively addresses this non-linearity issue. However, they examine large US Financial Holding Companies. FHCs provide completely different types of non-interest income than cooperative banks do: FHCs trade securities and derivatives, sell investment certificates and other trading assets who may incorporate high risk. Contrary, cooperative banks focus on commission income (fees) from monetary transactions, lending services and selling insurances. Thus, one can say that these activities may incorporate less risk. As the common measure of bank performance within this field (risk-adjusted returns) explicitly considers risk, this could mean that results from Stiroh and Rumble (2006) do not necessarily apply to cooperative banks. Moreover, FHCs also differ in structure and strategy largely from cooperative banks. This is what makes the underlying empirical analysis of the net effect of cooperative banks (by explicitly considering non-linearity) of particular interest.

2.3 Variables, Data and Empirical Research Method

2.3.1 Measures of Diversification

Following Stiroh (2004b), the author uses a revenue Herfindahl-Hirschman Index (HHI_{REV}) in order to measure diversification between major revenue streams for each bank:

$$HHI_{REV} = \left(\frac{NON}{NETOP}\right)^2 + \left(\frac{NET}{NETOP}\right)^2, \quad (1)$$

where NETOP equals NON plus NET (NETOP = NON + NET). NON is non-interest income, NET indicates net interest income, and NETOP is net operating revenue[8]. Banks with a high HHI are more concentrated and less diversified.

Following the same procedure, the author constructs measures of diversification within the lending (HHI_{LOAN}) and non-interest (HHI_{NON}) business as:

$$HHI_{LOAN} = \left(\frac{RE}{LOAN}\right)^2 + \left(\frac{MUN}{LOAN}\right)^2 + \left(\frac{CONS}{LOAN}\right)^2, \quad (2)$$

where LOAN equals RE plus MUN plus CONS (LOAN = MTG + MUN + CONS). LOAN captures total loans[9], RE is real estate lending, MUN is municipal loans, and CONS is consumer loans. A higher HHI_{LOAN} shows higher concentration within the loan portfolio.

$$HHI_{NON} = \left(\frac{COMM}{NON}\right)^2 + \left(\frac{TRADE}{NON}\right)^2 + \left(\frac{OTHER}{NON}\right)^2, \quad (3)$$

where NON equals COMM plus TRADE plus OTHER (NON = COMM + TRADE + OTHER). COMM is commission income, TRADE is trading income and OTHER is other operating income. Again, a higher HHI_{NON} shows more concentration within non-interest generating activities.

[8] Net operating revenue is a standard measure of bank revenue (Stiroh and Rumble, 2006; Mercieca et al., 2007).
[9] Total loans captures all loans within the loan portfolio except loans to other banks.

2.3.2 Measures of Risk-Adjusted Performance

In order to estimate the impact of diversification on risk-adjusted returns, bank performance measures that account for risk are applied. As the sample is about cooperative banks, no market data exists, since these banks are non-listed banks. Thus, the study focuses on common risk-adjusted measures based on accounting data. The author calculates a banks risk-adjusted return as follows: First, the author measures a banks return by calculating the mean return over the respective period. Second, the standard deviation of returns is the measure for bank risk. Consequently, the mean and standard deviation are calculated over all years a bank is observed (both measures are calculated for each bank individually). Following this procedure, the author calculates a banks risk-adjusted return (RAROE/ROROA) from its return on equity and return on assets as follows:

$$\text{RAROE} = \left(\frac{\overline{ROE}}{\sigma ROE}\right) \qquad \text{RAROA} = \left(\frac{\overline{ROA}}{\sigma ROA}\right), \tag{4}$$

where $\overline{\text{ROE}}$ captures the average return on equity (net income divided by equity) and $\overline{\text{ROA}}$ is the average return on assets (net income divided by total assets). The corresponding standard deviations are σROE and σROA. A higher value in risk-adjusted return indicates higher profitability.

Lastly, the author employs the Z-score to measure a banks insolvency risk. Mercieca et al. (2007), Stiroh (2004b) and Stiroh and Rumble (2006) all use the Z-score, which has been established by Boyd and Graham (1986). The ratio is an accounting based measure and indicates a bank's distance to default. Specifically, it measures how many standard deviations a bank's returns need to fall until they push a bank into insolvency (Stiroh and Rumble, 2006). Existing literature defines the Z-score as follows:

$$Z = \frac{\overline{ROA} + \overline{E/A}}{\sigma ROA}, \quad (5)$$

where $\overline{ROA}$ and σROA are again the mean and standard deviation of return on assets and $\overline{E/A}$ captures the mean equity to asset ratio (equity capital divided by total assets). Consequently, a higher Z-score indicates improved risk-adjusted performance.

2.3.3 Data and Descriptive Analysis

Since the sample in this study is a sample of non-listed banks, the author uses annual accounting data published in the German "Bundesanzeiger". The author hand-collected the data of 354 cooperative banking institutions and 1940 observations (from www.bundesanzeiger.de) from Germany with year-end balance sheet and income statement data from 2005 to 2010. The author decided to collect the data from 2005 to 2010 since this period covers the recent financial crisis. This period provides a setting of high differences in bank performance, which the author considered as beneficial for the underlying investigation. In order to obtain consistent data the author calculates the numbers in Table 2.2 as follows: Mergers may bias estimation results. For this reason, the author decided to drop all banks who were part of a merger. Eliminating mergers reduces the sample to 258 institutions and 1548 observations. Shares of interest income and non-interest income must be below 1.0. This is a prerequisite, as a share > 1 for one of these components leads to a meaningless HHI; in the case that this happens for a bank in a certain year that single observation was dropped. This reduces the sample to 1250 bank-year observations. Calculating mean values and requiring at least three observations per bank further reduces the sample size to 230 observations. [10] Due to outliers, the author decided to consider values of average return on

[10] In order to consider this issue the author employs observation dummies in the regressions.

equity (ROE) between the 3rd and 97th percentile only; This results in a final sample of 217 observations (one observation per bank).

Table 2.1 Sample Selection.

	Observations
Initial sample of cooperative banks from Germany with balance sheet and income statement data from 2005 to 2010 from the German "Bundesanzeiger".	1940
Less: Banks being part of a merger between 2005 and 2010.	-392
Less: Banks with an interest income and non-interest income share > 1.0.	-298
Less: Calculating mean values and requiring at least three observations per bank.	-1020
Less: Outliers (on a three percent level).	-13
Final Sample	217

According to Table 2.2, the average assets size of the sample is roughly about 300 Million Euro. The smallest institution in the sample has an asset size of 18 Million Euro and the largest institution has an asset size of almost 4 Billion Euro, which indicates that the sample contains small and medium sized banks. All three HHI show large variation; HHI_{REV} indicates that there are banks who are completely diversified (0.50). HHI_{LOAN} ranges from 0.45 to 0.96 indicating that there are banks with highly diversified as well as highly concentrated loan portfolios. The same accounts for HHI_{NON} but with the difference that there are banks completely concentrated (1.0) within non-interest generating activities.

Another important number is the non-interest income share, which ranges from 16.67% to 68.71%, indicating that there are banks who rely more on non-interest generating activities than on interest generating activities. The average non-interest income share is 30.45%.

Table 2.2 Descriptive statistics for German cooperative banks over the period 2005-2010.[11]

	Mean	Median	Standard Deviation	Minimum	Maximum
Components					
Average assets (€m)	294.14	207.26	375.34	18.18	3993.85
Return on average equity (%)	5.18	5.01	1.94	0.64	10.61
Return on average assets (%)	0.32	0.30	0.14	0.03	0.75
Equity to assets (%)	6.12	5.85	1.32	2.86	11.69
Loans to assets (%)	54.59	55.0	10.8	27.0	86.04
Diversification					
HHI_{REV}	0.59	0.59	0.04	0.50	0.72
HHI_{LOAN}	0.64	0.65	0.09	0.45	0.96
HHI_{NON}	0.58	0.54	0.11	0.41	1.00
Risk-adjusted performance					
RAROE	5.43	2.98	7.69	0.86	7.25
RAROA	4.53	2.93	4.78	0.83	3.49
Z-Score	123.78	64.01	218.42	13.37	2521.96
Non-interest income share of					
Net operating revenue (%)	30.45	29.67	6.38	16.67	68.71
Shares of non-interest income (%)					

[11] See Appendix A for detailed information about the variables used in Table 2.2.

Commission/non-interest	67.40	71.37	15.17	15.66	97.81
Trading/non-interest	0.48	0.08	1.79	0.00	24.79
Other/non-interest	32.12	28.43	15.22	1.69	84.34
Loan portfolio shares (%)					
Real estate/loans	42.84	43.09	20.20	0.00	85.93
Municipal/loans	2.24	1.13	3.12	0.00	26.80
Consumer/loans	32.12	28.43	15.22	1.69	84.34

Results are for 217 cooperative banks with minimum three annual observations from 2005 to 2010. All variables are calculated as averages for the underlying observations.

Within non-interest income generating activities there are banks who heavily rely on commission income (97.81%) and other income (84.34%), whereas no bank primarily relies on trading income (where the maximum share is 24.79%). Similar variation accrues to the loan portfolio: there are banks who heavily rely on real estate lending (85.93%) and other lending (84.34%), whereas the maximum share for municipal lending is 26.80%.

Due to these large variations, it is necessary to evaluate the link between strategic focus (business line exposure), diversification, and risk-adjusted performance.

2.4 Empirical Analysis

The empirical analysis starts with the measure of diversification across business lines, HHI_{REV}, because it covers all income generating activities. After this step, the author employs measures of diversification within business lines (HHI_{LOAN} and HHI_{NON}) in the

second stage of the regressions. On both levels, the author gauges the impact of a 1 percent increase in the non-interest share on risk-adjusted returns for various percentiles.[12]

2.4.1 Regression Model

The author applies OLS regressions to estimate the impact of diversification (measured by HHI_{REV}) on risk-adjusted returns. An important issue by using the HHI is that it is not clear which activity is responsible for a rising HHI. In this case, one can just observe that the bank becomes more concentrated. Put simply, a bank that earns all its revenues from interest generating activities would have the same HHI as a bank that generates all its revenues from non-interest activities. As these are completely different banking strategies, the author additionally controls for the type of revenue by including the share of non-interest income (NONSH). ROE, ROA, σROE, σROA, RAROE, RAROA, and Z-score are used as dependent variables (Y) in the regressions:

$$Y_i = \beta_0 + \beta_1 \overline{HHI_{REV_\iota}} + \beta_2 \overline{NONSH_\iota} + \beta_3 \overline{\left(\frac{L}{A}\right)_\iota} + \beta_4 \overline{\left(\frac{E}{A}\right)_\iota} \quad (6)$$

$$+\beta_5 ln\bar{A}_\iota + \beta_6 \overline{dln(A_\iota)} + \beta_7 \overline{dln(A_\iota)}^2 + \beta_8 OBS_i + e_i \,,$$

where bars over variables indicate average values for the number of observations per bank. Since averages are used, the author refers the empirical analysis as "between" regression, because differences in activity and focus across banks cause regression results (Stiroh, 2004b). The advantage of this approach is that random variation concerning the non-interest income share averages out and hence this approach uses a fairly precise measure of a bank's strategic focus (Stiroh and Rumble, 2006). Consequently, all variables in the regressions are

[12] See Stiroh and Rumble, 2006 who use the same approach in their analysis.

means or standard deviations calculated over all observations per bank, which leads to one observation per bank.[13] The coefficients in the regressions show conditional correlations between bank performance measures and diversification strategies and thus cannot be interpreted in a causal way.

According to Equation (6) HHI_{REV} is the revenue HHI and NONSH[14] is the non-interest income share. The author additionally considers differences in bank asset structure (the amount of loans compared to other interest generating activities etc.) by controlling for the ratio of loans to assets (L/A). Additionally, the author controls for the equity to asset ratio (E/A) and asset growth rates (squared to evaluate non-linearity) in order to consider risk preferences from the management. For instance, if the management is inclined to take on high risks these banks may hold less equity and have higher growth rates. The author controls for systematic differences in volatility over the observations per bank by applying observation dummy variables.[15]

The variables of interest are β_1 (measure of diversification) and β_2 (measure of increased non-interest income). First, since HHI_{REV} is a revenue diversification measure, the author expects β_1 to be positive in the ROE and ROA regressions in the case that concentration increases returns. Second, if diversification leads to reduced volatility of bank profits, the author expects β_1 to be positive in the corresponding risk measures (σROE, σROA). The coefficient β_2 captures the impact from a shift of interest income to non-interest income. In the case that non-interest income leads to higher returns than interest income, β_2 will be positive in the corresponding performance regressions (ROA, ROE). Therefore, if non-interest income leads to higher risk (higher volatility), β_2 will be also positive in the σROE and σROA regressions.[16]

[13] This is detrimental with regard to the point that bank-specific factors (within the bank) cannot be analyzed.
[14] Due to collinearity the interest income share is dropped in the regressions. Hence, the NONSH coefficient needs to be interpreted with regard to the omitted (interest income) share.
[15] OBS4 captures 4 observations, OBS5 captures 5 observations (OBS3 is omitted in order to avoid perfect collinearity).
[16] See Stiroh, 2004b.

As Mercieca et al. (2007) note, there are two effects arising from a shift towards non-interest income: First, a direct effect from increased non-interest income. Second, an indirect effect due to changes in revenue diversification. The resulting net effect of an increase in non-interest income depends on the strength of both effects. The direct and indirect effect are variance effects and the net effect is a covariance effect.[17]

Table 2.3 shows that β_1 is negative and significant on a 10% level in the ROE regression, which means that diversification leads to higher profitability. According to risk (σROE, σROA) the author does not find any significant effect of β_1 and β_2. This result might support the view that small banks do not operate in risky non-interest activities.

Column 5 and 7 of Table 2.3 show concentration benefits for the respective banks: banks who exhibit more concentrated revenue streams have higher risk-adjusted profits (RAROE) and a higher Z-score (distance to default). This applies to the finding of Goddard et al. (2008) who identify that revenue concentration increases risk-adjusted returns. With regard on insolvency risk, Stiroh (2004b) measures a positive but insignificant relation. However, at this point of evaluation one does not know whether concentration benefits arise from shifting from interest income to non-interest income or vice versa.

According to the NONSH coefficient, there is no significant effect in terms of return and risk. However, the coefficient of NONSH is positive in the RAROE and Z-score regression, indicating that shifting from interest income to non-interest income improves risk-adjusted returns and insolvency risk.

The loan-to-asset ratio indicates that those banks who hold more loans in their balance sheet are more profitable (column 1). At the same time, the positive impact of equity on returns shows that banks with higher equity perform better. Especially the ROE figure might be surprising within this context. Since this figure contains equity in the denominator, one may expect that banks with high shares of equity exhibit lower ROEs. However, results do

[17] See Appendix B for the calculation of the test-statistic of the direct, indirect and net effect.

Table 2.3 Return, risk and risk-adjusted return regressions.

	ROE	σROE	ROA	σROA	RAROE	RAROA	Z-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HHI_{REV}	-0.0888*	0.0147	-0.0045	-0.0020	39.6919***	14.0953	675.2531**
	(0.0530)	(0.0629)	(0.0049)	(0.0028)	(14.8603)	(11.1085)	(338.3377)
NONSH	-0.0485	0.0299	-0.0032	-0.0003	28.2309***	7.1506	371.8890*
	(0.0330)	(0.0430)	(0.0034)	(0.0017)	(9.6058)	(7.1786)	(210.2619)
Loans/Assets	0.0192*	-0.0087	0.0012*	-0.0002	4.8386*	4.3414**	6.2549
	(0.0097)	(0.0079)	(0.0006)	(0.0005)	(2.6299)	(2.0299)	(62.5286)
Equity/Assets	0.2094**	0.1600**	0.0575***	0.0228***	-25.2515	-17.8216	-1,374.8530**
	(0.0910)	(0.0732)	(0.0060)	(0.0049)	(24.4209)	(18.3080)	(584.7173)
Log (Assets)	0.0008	0.0014	0.0001	0.0001	0.4927	0.03426	1.2107
	(0.0012)	(0.0010)	(0.0001)	(0.0001)	(0.3337)	(0.2481)	(7.9520)
Asset Growth	0.3964***	0.1528***	0.0213***	0.0096***	-40.1642**	-9.4508	-1,008.2580**
	(0.0694)	(0.0568)	(0.0045)	(0.0037)	(18.6676)	(13.8858)	(443.8167)
Asset Growth^2	-1.1623***	-0.8742**	-0.0569**	-0.0387	281.1725**	70.7306	5,399.3610*
	(0.4401)	(0.3598)	(0.0288)	(0.0234)	(118.9437)	(89.0484)	(2,800.3830)
OBS4	-0.0044	-0.0014	-0.0001	-0.0002	-0.0059	-0.1332	17.0992
	(0.0030)	(0.0025)	(0.0002)	(0.0002)	(0.8187)	(0.6061)	(19.1680)
OBS5	-0.0005	0.0010	0.0002	0.0001	-0.3645	-0.6086	-14.5888

	(0.0029)	(0.0023)	(0.0002)	(0.0002)	(0.7824)	(0.5786)	(18.3654)
Constant	-0.0174	-0.0228	-0.0048	-0.0030	2.5510	6.1607	-342.1773
	(0.0286)	(0.0245)	(0.0019)	(0.0015)	(7.7653)	(5.7964)	(182.5867)
F-Test	6.98***	2.43**	15.95***	5.02***	2.71***	1.19	2.98***
Observations	217	217	217	217	217	217	217
R-squared	0.2328	0.0955	0.4095	0.1792	0.1053	0.0491	0.1147

The author applies OLS regressions for all cooperative banks with minimum three annual observations. All variables are means within the 3rd and 97th percentile. In order to obtain adequate HHIs the author only considers average shares of non-interest income between 0.0 and 1.0. Robust standard errors are in parentheses (*, **, *** capture 10%, 5% and 1% of statistical significance).

not show this notion: banks with high shares of equity appear to have higher returns compared to other banks. Since returns build up equity this may explain why banks with high equity also tend to exhibit higher ROEs.

Results also show that fast growing banks are more profitable (ROE and ROA) but also more risky (σROE and σROA). Thus, asset growth appears to drive up volatility. Considering the data, there are shrinking banks (the minimum asset growth equals -4.11%) and fast growing (the maximum asset growth equals 19.28%) banks. The asset growth squared figure indicates an inverted U-shaped relation between asset growth and risk, with a maximum of 8.74% for this relationship (see Appendix C). Nevertheless, there are only 8 observations with an asset growth higher than the mentioned maximum (and only 4 observations exhibit an asset growth higher than 10%). Consequently, one can argue that asset growth indeed drives up bank risk. Similarly, results reveal a U-shaped relationship between asset growth and risk-adjusted returns (RAROE). The negative relationship turns positive at a minimum of 7.14%. Thus, the negative effect increases for 198 of the 217 observations, hence for most of the sample banks. Taken together, the negative effect of asset growth (risk) appears to dominate the positive effect (return) for most of the banks hence leading to a negative relationship between asset growth and risk-adjusted returns (RAROE and Z-score).

In order to take a more differentiated view the paper proceeds by evaluating the net effect for revenue diversification because the typical cooperative bank concentrates by increasing its interest income share. Thus, the following derivation is applied:

$$\frac{dy}{d\overline{NONSH}} = \widehat{\beta_1}\frac{d\overline{HHI_{REV}}}{d\overline{NONSH}} + \widehat{\beta_2}\,, \tag{7}$$

where the partial derivative is obtained from Equation (6). Therefore, Equation (7) shows the impact of an increase in the non-interest-income share on the dependent variable. This

evaluation leads to two effects: the first term captures the indirect effect and shows the impact of a one percent increase of the non-interest income share on diversification; the second term shows the direct effect of a one percent increase of the non-interest income share. Since there is a non-linear relationship between HHI_{REV} and NONSH, the net effect (which is the sum of the direct and indirect effect) depends on the point of evaluation concerning the non-interest income share used in equation 7.[18]

Table 2.4 shows results of the direct, indirect, and the net effect from the RAROE regression.[19] The values are results of the evaluation of the 5th, 25th, 50th, 75th, 90th and 95th percentile. These percentiles reflect average non-interest shares of 0.22, 0.26, 0.30, 0.33, 0.38 and 0.41. The direct effect is positive and significant: a one percent increase in the share of non-interest income improves risk-adjusted profits by 0.282. Since the estimated relationship is linear, this effect does not vary over the respective percentiles. The indirect effect varies from -0.444 to -0.137 and remains in all percentiles highly significant, hence indicating a negative diversification effect[20]. This means that a shift towards non-interest income is more detrimental for banks who are more concentrated on the interest business. This makes sense as Table 2.4 reports that concentration is beneficial.[21] Thus, the decrease in performance is stronger for banks who are less exposed to non-interest income. Put differently, banks who are already heavily exposed to non-interest income (90th and 95th percentile) do perceive just a small negative diversification effect by a further shift towards non-interest income.[22]

[18] The approach is based on the work of Stiroh and Rumble, 2006.

[19] Table 3 only reports regression results for RAROE, which is the authors preferred measure of risk-adjusted returns. Results for RAROA and Z-Score are similar: See Appendix D.

[20] See Appendix B for further details of the calculation of the diversification effect.

[21] For banks who have a non-interest share of >0.5 the indirect effect turns positive. This accounts for the 99th and 100th percentile. For these banks, a further shift towards non-interest income concentrates the revenue stream.

[22] The 95th percentile failed to be highly significant since the t-value is 2,582 which is <2,601. However, I also evaluated the 99th percentile, which is highly significant (t-value of 2,943).

Table 2.4 Estimates of a 1 percent increase in the non-interest share on RAROE.

Non-interest share percentiles	5th	25th	50th	75th	90th	95th
Direct effect	0.282***	0.282***	0.282***	0.282***	0.282***	0.282***
	(0.096)	(0.096)	(0.096)	(0.096)	(0.096)	(0.096)
Indirect effect	-0.444***	-0.373***	-0.324***	-0.266***	-0.196***	-0.137***
	(0.166)	(0.140)	(0.121)	(0.010)	(0.073)	(0.051)
Net effect	-0.162*	-0.091	-0.042	0.016	0.086*	0.146**
	(0.093)	(0.072)	(0.058)	(0.048)	(0.047)	(0.056)

Table 2.3, Column 5 provides the basis for this evaluation of the 5th, 25th, 50th, 75th, 90th and 95th percentile. These percentiles reflect average non-interest shares of 0.22, 0.26, 0.30, 0.33, 0.38 and 0.41. The direct effect shows the relation between the omitted variable (interest income) and the related non-interest income share for a 1 percent increase in the non-interest income share. The indirect effect measures the impact of a 1 percent increase of the non-interest income share on revenue diversification. The net effect is the sum of the direct and indirect effect. Robust standard errors are in parentheses (*, **, *** capture 10%, 5% and 1% of statistical significance).

The net effect, which is the sum of the direct and indirect effect, shows that only highly diversified banks (90th and 95th percentile) benefit by a further shift towards non-interest income. In this case, the direct effect dominates the indirect effect. This finding could confirm the view that banks who already built capabilities and expertise (indicated by a high share of non-interest income) benefit from shifting towards non-interest income.

With respect to the 5th percentile, the results show a significant negative net effect on the 10% level.[23] This may indicate that banks, which primarily generate interest income, should keep focusing on the interest business. Goddard et al. (2008) note that banks who have few revenue from non-interest income, lack knowledge and technology concerning non-interest generating activities. Thus, focus on interest income appears beneficial for these

[23] I also evaluated the 1st and 2nd percentile for RAROE, RAROA and Z-Score. The results in the RAROE regression show negative and significant effects for the 1st percentile on the 5% level and for the 2nd percentile on the 10% level. See Appendix E for detailed information.

banks. The other way round, banks who are already generating high shares of non-interest income could reap the benefits of knowledge and technology employed.

In summary, results in Table 2.4 show exactly the opposite from the study from Stiroh and Rumble (2006). This confirms the view that the results from commercial banks banks do not apply to cooperative banks.

2.4.2 Second Stage Regression

As interest and non-interest generating activities differ largely one might think of diversification benefits within these two categories. In order to address this issue the author extends the regression of Equation (6) as follows:

$$Y_i = \beta_0 + \beta_1\overline{HHI_{REV_\iota}} + \beta_2\overline{NONSH_\iota} + \beta_3\overline{HHI_{NONSH_\iota}} + \beta_4\overline{COMM_\iota} + \beta_5\overline{TRD_\iota} + \beta_6\overline{OTHER_\iota} + \beta_7\overline{HHI_{LOAN_\iota}} + \beta_8\overline{RE_\iota} + \beta_9\overline{MUN_\iota} + \beta_{10}\overline{CONS_\iota} + \beta_{11}\overline{\left(\frac{L}{A}\right)_\iota} + \beta_{12}\overline{\left(\frac{E}{A}\right)_\iota} + \beta_{13}ln\overline{A_\iota} + \beta_{15}\overline{dln(A_\iota)^2} + \beta_{16}OBS_i + e_i\,, \quad (8)$$

where the extension concerns particularly the two measures of diversification within the two major revenue streams (HHI_{NON}, HHI_{LOAN}). Corresponding component shares of non-interest income are included as well as the shares of the loan portfolio. All other variables remain the same like in Equation (6).

Table 2.5 shows that HHI_{REV} is positive and significant in the RAROE but not in the Z-score regression (t-value of 1,477<1,653). The same accounts for the non-interest share.

HHI_{NON} decreases returns (ROE and ROA) and bank risk (σROE): hence, revenue diversification within the non-interest income business appears to be beneficial with regard

on returns. However, this would also lead to higher risk. The resulting effect on net is not clear since the author does not measure any significant effect on the three risk-adjusted performance measures. Trading business is negative related to volatility, hence indicating that this type of business reduces bank risk. This, in turn, leads to a positive and significant influence on the RAROE and RAROA regressions revealing that shifting from commission income (the omitted variable) to trading income increases risk-adjusted returns for cooperative banks. Shifting non-interest income from commissions to other operating returns leads to declining returns and risk. With regard on risk-adjusted returns, results show a positive but insignificant relationship.

HHI_{LOAN} is not significant in any regression. In addition, there are no significant effects within the loan portfolio.[24] Real estate loans failed to be significant since the t-value is 1,589<1,653.

Table 2.6 shows estimates with respect to the net effect. The author does find significant direct and indirect effects for each percentile. However, the author does not find any significant net effect.[25]

[24] Consumer loans is the omitted variable.

[25] The 5th percentile failed to be significant since the t-value is 1,632<1,653. However, there is a significant negative net effect for the 1st, 2nd percentile and a significant positive net effect for the 99th and 100th percentile on the 10% level. See Appendix F for detailed information.

Table 2.5 Estimates of all three diversification measures and corresponding component shares.

	ROE	σROE	ROA	σROA	RAROE	RAROA	Z-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HHI_{REV}	0.0128	0.1267*	0.0068	0.0011	32.7113**	11.7321	600.8409
	(0.0622)	(0.0750)	(0.0060)	(0.0033)	(16.5129)	(12.7803)	(406.7926)
NONSH	0.0640	0.1314**	0.0077	0.0027	21.1930*	4.7362	296.7793
	(0.0471)	(0.0577)	(0.0047)	(0.0025)	(12.4658)	(9.6607)	(307.1111)
HHI_{NON}	-0.0539**	-0.0370**	-0.0038***	-0.0019	8.3308	3.9246	59.7979
	(0.0218)	(0.0183)	(0.0014)	(0.0012)	(5.9353)	(4.6263)	(143.4510)
Trading/non-interest	-0.0886	-0.1480**	-0.0086	-0.0089**	70.0691***	27.1519*	379.8099
	(0.0721)	(0.0600)	(0.0093)	(0.0038)	(19.0778)	(14.7059)	(469.8494)
Other/non-interest	-0.0536***	-0.0326**	-0.0037***	-0.0014*	3.6255	1.6276	33.9953
	(0.0161)	(0.0136)	(0.0011)	(0.0009)	(4.3365)	(3.4088)	(105.5972)
HHI_{LOAN}	0.0061	0.0054	0.0004	0.0006	-2.6101	-2.2604	-21.0822
	(0.0119)	(0.097)	(0.0008)	(0.0006)	(3.1951)	(2.5056)	(78.1465)
Real estate/Loans	0.0063	0.0022	0.0005	0.0003	-2.8401	-1.9271	-19.4936
	(0.0068)	(0.0055)	(0.0004)	(0.0004)	(1.7870)	(1.3917)	(43.6451)
Municipal/Loans	0.0139	0.0264	0.0029	0.0036	-4.7389	-9.6707	-34.9599
	(0.0412)	(0.0335)	(0.0028)	(0.0022)	(10.7571)	(8.1374)	(267.0549)
Loans/Assets	0.0147	-0.0029	0.0011	-0.0002	6.3431**	4.8148**	15.4886

	(0.0102)	(0.0083)	(0.0007)	(0.0006)	(2.7083)	(2.1517)	(66.9232)
Equity/Assets	0.2280**	0.1552**	0.0574***	0.0227***	-18.3918	-15.0050	-1,346.1490**
	(0.0909)	(0.0736)	(0.0060)	(0.0050)	(24.0640)	(18.6089)	(598.1033)
Log (Assets)	-0.0002	0.0013	0.0001	0.0001	0.2276	-0.0714	0.0441
	(0.0013)	(0.0011)	(0.0001)	(0.0001)	(0.3498)	(0.2691)	(8.7247)
Asset Growth	0.4164***	0.1486**	0.0229***	0.0090**	-26.5600	-5.4300	-946.8904**
	(0.0703)	(0.0580)	(0.0045)	(0.0038)	(18.6377)	(14.2728)	(461.8319)
Asset Growth²	-1.3258***	-0.8540**	-0.0706**	-0.0334	179.2478	34.0533	4,912.8210*
	(0.4500)	(0.3718)	(0.0230)	(0.0243)	(120.0581)	(92.8158)	(2,950.1480)
OBS4	-0.0045	-0.0020	-0.0002	-0.0002	0.5918	0.0771	20.4420
	(0.0030)	(0.0025)	(0.0002)	(0.0002)	(0.8096)	(0.6183)	(19.7855)
OBS5	0.0008	0.0009	0.0003	0.0001	0.2305	-0.3862	-12.0312
	(0.0030)	(0.0024)	(0.0002)	(0.0002)	(0.7920)	(0.6061)	(19.3561)
Constant	0.0409	-0.1013*	-0.0059	-0.0028	-31.7520**	-5.2586	-283.7442
	(0.0527)	(0.0599)	(0.0047)	(0.0029)	(14.2531)	(10.8897)	(343.2873)
F-Test	5.09***	2.10**	10.72***	3.53***	2.96***	1.05	1.81**
Observations	217	217	217	217	217	217	217
R-squared	0.2754	0.1354	0.4445	0.2083	0.1809	0.0729	0.1189

The author applies OLS regressions for all cooperative banks with minimum three annual observations. All variables are means within the 3rd and 97th percentile. In order to obtain adequate HHIs the author only considers average shares of non-interest income between 0.0 and 1.0. Robust standard errors are in parentheses (*, **, *** capture 10%, 5% and 1% of statistical significance).

Taken together the results show evidence of concentration benefits for cooperative banks in Germany between broad activity classes but not within them. The author finds that non-interest income leads to higher risk-adjusted returns than interest income. On net, shifting towards non-interest income is beneficial for banks who already hold high shares of non-interest income (90^{th} and 95^{th} percentile). At the same time, there is a significant negative net effect for the 5^{th} percentile, which may indicate that banks which generate primarily interest income should keep focusing on the interest business. As there is no significant effect for the percentiles "in between", this may belong to the argument of DeYoung and Rice (2004) who state that banks need time to build capabilities and expertise in order to engage in a profitable non-interest business.

Some of the results apply and others are contrary to the existing literature in this field: The positive concentration effect is in line with the study from Goddard et al. (2008) who identified the same effect for US credit unions. This makes sense as credit unions have a similar business model and revenue structure as cooperative banks. The positive relation between non-interest income and risk-adjusted returns is contrary to most of the studies in this field (Mercieca et al., 2007; Stiroh, 2004b; Stiroh and Rumble, 2006). Goddard et al. (2008) measure a positive but insignificant relation between non-interest income and risk-adjusted returns. Lastly, most of the studies in this field identify a negative net effect at the 50^{th} percentile. The author also finds a negative but insignificant net effect for the 50^{th} percentile.

However, this study goes beyond the studies mentioned above in the way that the author explicitly considers non-linearity in the net effect. As previously mentioned, there is solely the study from Stiroh and Rumble (2006) that comprehensively addresses non-linearity concerning the net effect as the author does. Their results are mirror-inverted to mine: In their analysis of large US FHCs, they find diversification benefits between broad activity classes. They further identify that non-interest income decreases risk-adjusted returns.

Table 2.6 Estimates of a 1 percent increase in the non-interest share on RAROE.

Non-interest share percentiles	5th	25th	50th	75th	90th	95th
Direct effect	0.2119*	0.2119*	0.2119*	0.2119*	0.2119*	0.2119*
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
Indirect effect	-0.366**	-0.308**	-0.267**	-0.219**	-0.162**	-0.113**
	(0.185)	(0.155)	(0.135)	(0.111)	(0.082)	(0.057)
Net effect	-0.154	-0.096	-0.055	0.008	0.050	0.099
	(0.094)	(0.073)	(0.063)	(0.058)	(0.065)	(0.079)

Table 2.5, Column 5 provides the basis for this evaluation of the 5th, 25th, 50th, 75th, 90th and 95th percentile. These percentiles reflect average non-interest shares of 0.22, 0.26, 0.30, 0.33, 0.38 and 0.41. The direct effect shows the relation between the omitted variable (interest income) and the related non-interest income share for a 1 percent increase in the non-interest income share. The indirect effect measures the impact of a 1 percent increase of the non-interest income share on diversification. The net effect is the sum of the direct and indirect effect. Robust standard errors are in parentheses (*, **, *** capture 10%, 5% and 1% of statistical significance).

However, their most important finding is that FHCs who already hold high shares of non-interest income do not benefit (negative net effect) by further shifts towards non-interest income, because the negative effect from more non-interest income dominates the positive diversification effect. They state that highly diversified banks "may have overestimated the benefits of diversification".

The author addresses these diverging results to several issues: First, they investigate large FHCs who differ largely from a sample of cooperative banks with respect to their business model and structure. A not negligible factor might be that FHCs are listed banks and cooperative banks are not. Consequently, this causes exposure of FHCs to short-term

macroeconomic developments, which may increase volatility of the non-interest business. Since risk is measured as the volatility of bank profits this may be an explanation for their diverging results regarding non-interest income. Second, the different types of non-interest income between these two samples: FHCs trade securities, sell investment certificates and other trading assets, which may incorporate high idiosyncratic risk. Contrary, cooperative banks focus on commission income (fees) from monetary transactions, lending services and selling insurances. Thus, one can say that these activities may incorporate less idiosyncratic risk. Third, the market where FHCs operate in may be more competitive and hence yield lower returns in the non-interest business.

Finally, one potential reason for the finding of concentration benefits between activity classes but not within them could be that management skills and business practices are less transferable between broad activity classes. Within activity classes, this issue might not play an important role since lending activities for, e.g., real estate lending and municipal lending require similar skills. This explanation is similar to DeLong (2001), who identified positive stock market reactions for mergers who focused on one major source of revenue.

2.5 Summary and limitations

This study analyzes the link between diversification and risk-adjusted performance for cooperative banks. The author shows that the results from commercial banks from the study of Stiroh and Rumble (2006) do not apply to a sample of cooperative banks. Differences in the business model and in particular the revenue streams appear to determine different outcomes. Results show that concentration relates positively to risk-adjusted returns. At the same time, non-interest income is more profitable than interest income. The evaluation of the underlying non-interest income share shows that banks, who heavily rely on non-interest income benefit by shifting towards non-interest income. This finding accrues due to the fact, that in this case the positive direct effect dominates the negative indirect effect, leading in a

positive (and significant) net effect. Furthermore, the author identifies a negative net effect for banks who are heavily exposed to interest generating activities. This means, that shifting to non-interest income decreases risk-adjusted returns for these banks. Consequently, these banks do better by focusing on the interest business. Overall, results may also show evidence that banks need time to build capabilities, expertise and experience before trading off return and risk efficiently with regard on the non-interest business, which confirms the view of DeYoung and Rice (2004).

Positive non-interest income perspectives reason the trend mentioned at the beginning of the paper that banks all over the world keep shifting business towards non-interest income since two decades. The author shows that this also applies to the cooperative banking sector in Germany. Due to increased competition banks search for new revenue streams in order to remain competitive. Results show, that by doing so only banks who gained already experience are able to increase profitability. The other way round, banks who focus on interest income need to be aware that they may need time to establish a profitable non-interest business.

Appendix

Appendix A

Variable	Description
ROE	Net income divided by equity
ROA	Net income divided by assets
NET	Net operating income, which equals the sum of net interest income And non-interest income
NONSH	Non-interest income share, which is calculated as non-interest income divided by net operating income
INTSH	Interest income share, which is calculated as net interest income divided by net operating income
COMM	Commission income, which is calculated as the share of commission income in non-interest income
TRADE	Trading income, which is calculated as the share of trading income in non-interest income
OTHER	Other operating income, which is calculated as the share of other operating income in non-interest income
RE	Real estate loans, which is calculated as the share of real estate loans to total loans
MUN	Municipal loans, which is calculated as the share of municipal loans to total loans
CONS	Consumer loans, which is calculated as the share of consumer loans to total loans

Appendix B

$$HHI_{REV} = \left(\frac{NON}{NETOP}\right)^2 + \left(\frac{INT}{NETOP}\right)^2$$

⇨ $HHI_{REV} = INTSH^2 + NONSH^2$

⇨ $HHI_{REV} = (1 - NONSH)^2 + NONSH^2$

$$Y_i = \beta_0 + \beta_1\overline{HHI_{REV\iota}} + \beta_2\overline{NONSH\iota} + \beta_3\overline{\left(\frac{L}{A}\right)} + \beta_4\overline{\left(\frac{E}{A}\right)_\iota} + \beta_5 ln\bar{A}_\iota$$
$$+ \beta_6\overline{dln(A_\iota)} + \beta_7\overline{dln(A_\iota)^2} + \beta_8 OBS_i + e_i ,$$

Concentration (HHI_{REV}):

$$\frac{dy}{dNONSH} = (\widehat{\beta_1}(-2 + 4NONSH) + \widehat{\beta_2}) \times 0{,}01$$

Diversification (DIV = 1 - HHI_{REV}):

$$\frac{dy}{dNONSH} = (\widehat{\beta_1}(2 - 4NONSH) + \widehat{\beta_2}) \times 0{,}01$$

The coefficient in the regression in Table 2.3 would turn negative in the case that DIV (instead of HHI_{REV} as a measure for concentration) is the independent variable. However, since the derivation of DIV is the basis to calculate the indirect effect and net effect, results

show that signs change at this point of evaluation as well. Thus, applying the derivation of DIV to calculate the indirect effect and net effect equalizes the opposite sign of DIV as independent variable in Table 2.3. Consequently, results for the indirect and net effect of Table 2.3 can be interpreted either in the context of concentration or in the context of diversification respectively.

Test statistic of the direct effect:

$$\frac{\widehat{\beta_2}\times 0{,}01}{0{,}01\times\sqrt{(Var(\widehat{\beta_2}))}}$$

Test statistic of the indirect effect:

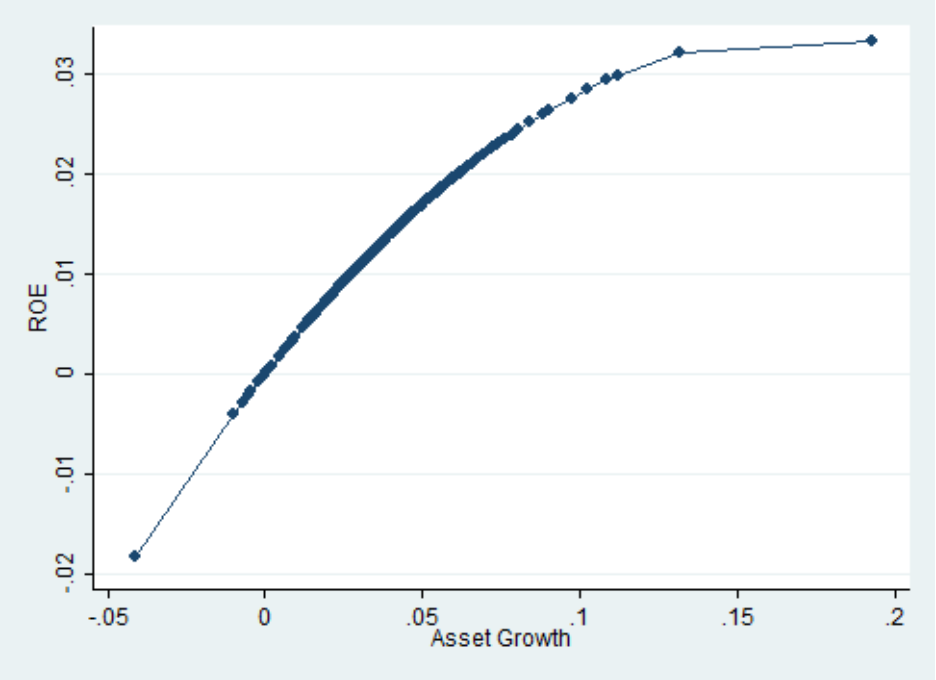
$$\frac{\widehat{\beta_1}\times(-2+4NONSH)\times 0{,}01}{0{,}01\times\sqrt{(-2+4NONSH)^2\times Var(\widehat{\beta_1})}}$$

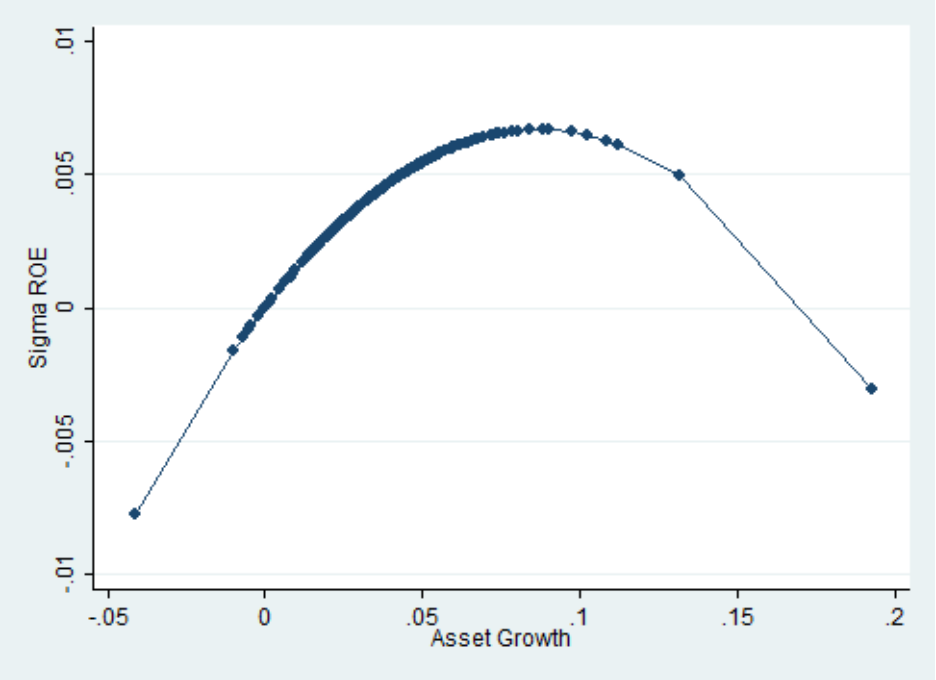
Test statistic of the net effect:

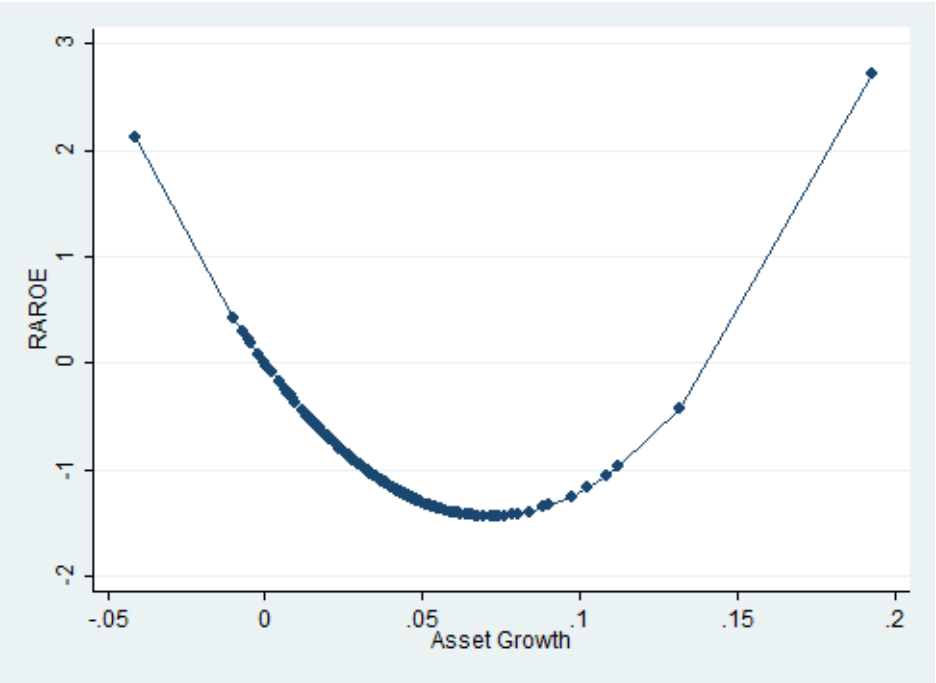
$$\frac{(\widehat{\beta_1}\times(-2+4NONSH)+\widehat{\beta_2})\times 0{,}01}{0{,}01\times\sqrt{(-2+4NONSH)^2\times Var(\widehat{\beta_1})+Var(\widehat{\beta_2})+2\times(-2+4\widehat{NONSH})\times Cov(\widehat{\beta_1},\widehat{\beta_2})}}$$

Appendix C

Non-linear effects of asset growth:






RAROE
3
2
1
0
-1
-2
-.05
0
.05
.1
.15
.2
Asset Growth

Appendix D

First-Stage Regressions:

Estimates of a 1 percent increase in the non-interest share on RAROA:

Non-interest share percentiles	5th	25th	50th	75th	90th	95th
Direct effect	0.141*	0.141*	0.141*	0.141*	0.141*	0.141*
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
Indirect effect	-0.158	-0.133	-0.115	-0.095	0.070	0.049
	(0.124)	(0.105)	(0.091)	(0.075)	(0.055)	(0.038)
Net effect	-0.017	0.008	0.026	0.046	0.071**	0.092**
	(0.070)	(0.053)	(0.044)	(0.036)	(0.035)	(0.042)

Table 2.3, Column 6 provides the basis for this evaluation. The direct effect shows the relation between the omitted variable (interest income) and the related non-interest income share for a 1 percent increase in the non-interest income share. The indirect effect measures the impact of a 1 percent increase of the non-interest income share on diversification. The net effect is the sum of the direct and indirect effect. Robust standard errors are in parentheses (*, **, *** capture 10%, 5% and 1% of statistical significance).

Estimates of a 1 percent increase in the non-interest share on Z-Score:

Non-interest share percentiles	5th	25th	50th	75th	90th	95th
Direct effect	3.719*	3.719*	3.719*	3.719*	3.719*	3.719*
	(2.103)	(2.103)	(2.103)	(2.103)	(2.103)	(2.103)
Indirect effect	-7.551*	-6.353**	-5.512**	-4.531**	-3.336**	-2.327**
	(3.784)	(3.183)	(2.762)	(2.270)	(1.672)	(1.166)
Net effect	-3.832*	-2.635	-1.793	-0.812	0.382	1.392
	(2.207)	(1.700)	(1.389)	(1.121)	(1.044)	(1.228)

Table 2.3, Column 7 provides the basis for this evaluation. The direct effect shows the relation between the omitted variable (interest income) and the related non-interest income share for a 1 percent increase in the non-interest income share. The indirect effect measures the impact of a 1 percent increase of the non-interest income share on diversification. The net effect is the sum of the direct and indirect effect.

Appendix E

First-Stage Regressions:

Estimates of a 1 percent increase in the non-interest share on RAROE:

Non-interest share percentiles	1st	2nd	50th	75th	99th	100th
Direct effect	0.282***	0.282***	0.282***	0.282***	0.282***	0.282***
	(0.096)	(0.096)	(0.096)	(0.096)	(0.096)	(0.096)
Indirect effect	-0.529***	-0.498***	-0.324***	-0.266***	0.025***	0.119***
	(0.198)	(0.186)	(0.121)	(0.010)	(0.010)	(0.045)
Net effect	-0.247**	-0.216*	-0.042	0.016	0.308***	0.401***
	(0.112)	(0.111)	(0.058)	(0.048)	(0.105)	(0.137)

Table 2.3, Column 5 provides the basis for this evaluation. The direct effect shows the relation between the omitted variable (interest income) and the related non-interest income share for a 1 percent increase in the non-interest income share. The indirect effect measures the impact of a 1 percent increase of the non-interest income share on diversification. The net effect is the sum of the direct and indirect effect. Robust standard errors are in parentheses (*, **, *** capture 10%, 5% and 1% of statistical significance).

Estimates of a 1 percent increase in the non-interest share on RAROA:

Non-interest share percentiles	1st	2nd	50th	75th	99th	100th
Direct effect	0.141*	0.141*	0.141*	0.141*	0.141*	0.141*
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
Indirect effect	-0.188	-0.177	-0.115	-0.095	0.009	0.042
	(0.148)	(0.139)	(0.091)	(0.075)	(0.007)	(0.033)
Net effect	-0.047	-0.036	0.026	0.046	0.150*	0.183*
	(0.091)	(0.083)	(0.044)	(0.036)	(0.078)	(0.102)

Table 2.3, Column 6 provides the basis for this evaluation. The direct effect shows the relation between the omitted variable (interest income) and the related non-interest income share for a 1 percent increase in the non-interest income share. The indirect effect measures the impact of a 1 percent increase of the non-interest income share on diversification. The net effect is the sum of the direct and indirect effect. Robust standard errors are in parentheses (*, **, *** capture 10%, 5% and 1% of statistical significance).

Estimates of a 1 percent increase in the non-interest share on Z-Score:

Non-interest share percentiles	1st	2nd	50th	75th	99th	100th
Direct effect	3.719*	3.719*	3.719*	3.719*	3.719*	3.719*
	(2.103)	(2.103)	(2.103)	(2.103)	(2.103)	(2.103)
Indirect effect	-9.003**	-8.473**	-5.512**	-4.531**	0.433**	2.026**
	(4.511)	(4.245)	(2.762)	(2.270)	(0.217)	(1.015)
Net effect	-5.285*	-4.754*	-1.793	-0.812	4.152*	5.746*
	(2.871)	(2.625)	(1.389)	(1.121)	(2.294)	(3.029)

Table 2.3, Column 7 provides the basis for this evaluation. The direct effect shows the relation between the omitted variable (interest income) and the related non-interest income share for a 1 percent increase in the non-interest income share. The indirect effect measures the impact of a 1 percent increase of the non-interest income share on diversification. The net effect is the sum of the direct and indirect effect. Robust standard errors are in parentheses (*, **, *** capture 10%, 5% and 1% of statistical significance).

Appendix F

Second-Stage Regression:

Estimates of a 1 percent increase in the non-interest share on RAROE:

Non-interest share percentiles	1st	2nd	50th	75th	99th	100th
Direct effect	0.2119*	0.2119*	0.2119*	0.2119*	0.2119*	0.2119*
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
Indirect effect	-0.436**	-0.410**	-0.267**	-0.219**	0.021**	0.098**
	(0.220)	(0.207)	(0.135)	(0.111)	(0.011)	(0.050)
Net effect	-0.224*	-0.199*	-0.055	0.008	0.233*	0.310*
	(0.124)	(0.113)	(0.063)	(0.058)	(0.134)	(0.170)

Table 2.5, Column 5 provides the basis for this evaluation. The direct effect shows the relation between the omitted variable (interest income) and the related non-interest income share for a 1 percent increase in the non-interest income share. The indirect effect measures the impact of a 1 percent increase of the non-interest income share on diversification. The net effect is the sum of the direct and indirect effect. Robust standard errors are in parentheses (*, **, *** capture 10%, 5% and 1% of statistical significance).

3 Does low Efficiency turn into high Risk? An Empirical Examination of Cooperative Banks

Abstract

The authors use Granger-causality-techniques in order to evaluate inter-temporal relationships between risk, efficiency and capital. Specifically, the authors estimate how credit risk, liquidity risk and capital risk relate to bank efficiency. The authors use two different measures for bank efficiency, namely cost and profit efficiency, since these measures reflect different managerial abilities. One is the ability to manage costs and the other is to maximize profits. Our results mostly apply to current literature in this field since the authors find that lower cost and profit-efficiency Granger-cause increases in credit risk. At the same time, the authors identify that credit risk negatively Granger-causes cost and profit-efficiency, hence revealing a bi-directional relationship between these measures. However, results also show a positive relationship between capital and credit risk, thus displaying that moral hazard (due to limited liability and deposit insurance) does not apply to our sample of cooperative banks. These findings may be important to regulators who should consider banks' business model when introducing new regulatory constraints.

Co-Author: Markus Stralla

JEL classification: G21, D24, C23, E44

Keywords: Efficiency, Risk, Capital

3.1 Introduction

There has been rising competition in the European banking market due to technological development, deregulation and the introduction of the Euro as a common currency in recent decades. In order to remain competitive banks were forced to improve efficiency. That is, banks try to operate closer to a "best practice" production function in the sense that banks improve the input – output relation. The key question in this context is if banks improve efficiency at a cost of higher risk to compensate decreasing earnings. When it comes to 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 (Barr and Siems, 1994; Demirgüc-Kunt, 1989). According to efficiency, studies show that the average bank generates low profits and incorporates high costs compared to the "best practice" production frontier (Fiordelisi et al., 2011; Williams, 2004). At first glance, these two issues do not seem related. However, Berger and DeYoung (1997) show that banks with poor management are less able to handle their costs (low cost-efficiency) as well as to monitor their debtors in an appropriate manner 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 to prevent negative consequences in the banking market.

The authors delve deeper into these ties as the authors first address 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. Contrary, economic downturns may negatively affect bank efficiency: increases in non-

performing loans may precede decreases in bank efficiency, as banks need to provide additional funds in order to handle increasing problem loans. Second, the authors address how these issues relate 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 might be 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 (Fiordelisi et al., 2011). Thus, the authors address these issues by explicitly investigating inter-temporal relationships between efficiency, risk and capital.

The authors contribute to existing literature in several ways: first, the authors use contemporaneous data of cooperative banks in Germany from 2005 to 2010. The sample period covers the recent financial crisis. Especially cooperative banks weathered the crisis better than other banks. For this reasons, it may be of particular interest whether results from previous literature apply to our sample of cooperative banks. For instance, the business model of cooperative banks is based on the interests of its commonly local customers (the cooperative act: § 1 GenG). This may imply that the common perception of banks engaging in moral hazard behavior may not apply to cooperative banks. Since short-term shareholder interests play no role for cooperative banks this may support this notion. Second, cooperative banks play a major role in many developed countries. Hence, investigating this bank type in terms of the relationships between efficiency, risk and capital may reveal helpful insights for e.g. regulators or supervisors. Third, liquidity has been widely neglected in the existing literature, since the common perception has been that access to additional liquid funds is not an issue. However, the recent financial crisis revealed that liquidity dried up for many banks due to increased mistrust in the banking sector. For this reason, the authors employ a measure for liquidity risk in order to evaluate how liquidity risk relates to efficiency and capital.

The paper proceeds as follows: Section 3.2 reviews current banking literature and provides relevant hypotheses. Section 3.3 describes the efficiency-models and the GMM-

estimation techniques. Section 3.4 provides information about the variables employed and descriptive statistics. Section 3.5 shows empirical results. The paper concludes by a summary of our most important findings.

3.2 Literature and Hypotheses

3.2.1 Literature Review

There have been two major strands in the banking literature at the beginning of the 1990s. One of them addressed the determinants of bank risk and especially the determinants of bankruptcy (Barr and Siems, 1994; Whalen, 1991). The other one investigates factors of bank efficiency (Berger, 1993; Berger and Humphrey, 1992). Berger and DeYoung (1997) brought these two strands together by positing that bank risk and efficiency relate to each other. That is, when analyzing the determinants of bank risk one needs to consider efficiency and vice versa. The authors investigate US commercial banks between 1985 and 1994 with regard on 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 inter-temporal relationships between problem loans, cost efficiency, and capital. The two most important results are the bi-directional negative relationship between problem loans and cost efficiency. That is, 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 capital are related hence require simultaneous estimations. Thus, they analyze 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 efficient 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 "robustness test" to the study from Berger and DeYoung (1997). Similar to Berger and DeYoung (1997) the author applies Granger-causality methods to investigate the relationship between problem loans, efficiency and capital. Due to data limitations, the author uses loan loss provision as a proxy for non-performing loans. Additionally, he employs the ratio of loans-to-assets as an indicator of credit risk. Moreover, he moves beyond the study from Berger and DeYoung (1997) by employing profit efficiency as a robustness test for cost efficiency. 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 analyze the relationships between efficiency (cost, profit and revenue), capital and bank risk. To the best of our knowledge, this is the only existing study that employs Granger-causality estimations in a GMM framework. Besides they use various measures of bank capital ([1] total capital as the sum of tier 1 and tier 2 capital, [2] book value of equity capital) and bank risk ([1] the classical measure of non-performing loans, [2] one-year and five-year ahead expected default frequency (EDF) as a forward looking measure of bank risk). Results indicate that decreases in cost and revenue efficiency precede higher bank risk and increases in bank capital Granger-cause cost efficiency improvements. In addition, 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) analyze bank efficiency with regard on ownership-type: Goddard et al. (2014) analyze the evolution of the average rank cost efficiency by a sample of 419 banks from Latin America over the period 1985 to 2010. 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 in dealing with cross-firm heterogeneity when estimating cost efficiency. They identify differences across countries in terms of bank cost efficiency. In addition, results show differences in cost efficiency for state-owned, privately owned and foreign banks. Berger et al. (2009) analyze profit and cost efficiency differences with regard on ownership-type of 38 Chinese banks between 1994 and 2003. They apply pooled estimations and find that foreign minority ownership increases efficiency (compared to no 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 least efficient.

Taken together, existing banking literature in this field is rather clear. Berger and DeYoung (1997), Williams (2004) and Fiordelisi et al. (2011) are the relevant studies who apply Granger-causality to disentangle the relationship between 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 considered this issue hence using a GMM framework for their estimations.

3.2.2 Research Hypotheses

In the following, the authors refer to relevant hypotheses for our study by building on previous studies from Berger and DeYoung (1997), Williams (2004) and Fiordelisi et al. (2011). In order to disentangle inter-temporal relationships between risk, efficiency and bank capital the authors 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 relatively high 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 who 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. Thus, the authors postulate our first hypothesis as:

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

The “bad luck” hypothesis assumes that economic downturns like the recent financial crisis in 2007 induce higher shares of non-performing loans. Since exogenous events are the basis for this hypothesis, changes in the loan portfolio do not relate to managerial failures. However, increases in non-performing loans will cause managers to tackle these problems, which will result in rising costs. Consequently, the authors define the second hypothesis as:

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

The “cost skimping” hypothesis relates to bank cost efficiency. Hereby one 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 lower quality of the loan portfolio in future periods. Given this scenario, banks appear to be efficient in controlling their costs at a cost of future bank risk. Thus, the authors define the “cost skimping” hypothesis as:

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

Lastly, the authors refer to the "moral hazard" hypothesis, which relates to bank capital. In this scenario, one assumes that banks who exhibit a low level of capital are inclined to take on more risk. The reason for this assumption is justified by agency-conflicts in banks between managers and shareholders. Specifically, bank managers are inclined to take more risk than is in the best interest of the owners (especially when they do not hold own shares). Besides, limited liability and deposit insurance programs may strengthen risk-taking incentives. Contrary, banks with high levels of capital may have reduced "moral hazard" incentives and hence be inclined to take on less risk. Thus, the authors postulate the "moral hazard" hypothesis as:

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

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

3.3 Methodology

According to previous studies in this field, the authors employ a two-step model to examine the aforementioned relationships between bank risk, capital and efficiency. In the first step, the authors 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 in order to investigate intertemporal relationships between bank risk, capital and efficiency.

3.3.1 Measuring Efficiency

In order to estimate efficiency levels, the authors employ the stochastic frontier approach (SFA) following Battese and Coelli (1995).[26] For cost efficiency, the authors estimate the following model:

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

where *i* specifies the bank, *t* denotes the time dimension, TC are total costs, $\mathbf{x}_i$ is a mx1 vector of input prices and outputs involved in the ith bank operations, $\boldsymbol{\beta}$ is a 1xm vector consisting of yet to estimate coefficients. The error term $\boldsymbol{\varepsilon}_{i,t}$ 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, σ_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(μ_U, σ_U^2). As in existing literature, the authors use a translog function form to estimate the frontier:

[26] The stochastic frontier has been estimated using the Stata command *sfpanel* written by Belotti et al. (2012).

$$lnTC = \alpha_0 + \sum_{j=1}^{3} \beta_j ln\, y_j + \sum_{j=1}^{3} \gamma_j ln\, w_j + \eta_1 E + \theta_1 T + \frac{1}{2}\left[\sum_{j=1}^{3}\sum_{k=1}^{3} \beta_{jk}\, ln\, y_j\, ln\, y_k + \sum_{j=1}^{3}\sum_{k=1}^{3} \gamma_{jk}\, ln\, w_j\, ln\, w_k + \eta_{11} E^2 + \theta_{11} T^2\right] + \sum_{j=1}^{3}\sum_{k=3}^{3} \lambda_{jk}\, ln\, y_j\, ln\, w_k + \sum_{j=1}^{3} o_j\, ln\, y_j\, E + \sum_{j=1}^{3} \rho_j\, ln\, y_j T + \sum_{j=1}^{3} \tau_j\, ln\, w_j\, E + \sum_{j=1}^{3} \varphi_j\, ln\, w_j T + ln\, \upsilon_{i,t} + ln\, u_{i,t} \quad (2)$$

i, *t* and TC remain defined as before. Y_j (*j*=1, 2, 3) are outputs, w_j (*j*= 1, 2, 3) are input prices, E is equity scaled by total assets, T is the time trend, $\upsilon_{i,t}$ 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). The authors define input prices 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 the variables included in Equation (2), the authors use two environmental variables z_i (*i*=1, 2), namely the ECB interest rate[27] (z_1) and GDP growth (z_2), to simultaneously model the inefficiency distribution:

$$\mu_u = \psi_0 + \psi_1 z_1 + \psi_2 z_2 \quad (3)$$

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

[27] The authors calculated the ECB interest rate as daily weighted values for each year.

(1) Standard symmetry

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

(2) Coefficient constrains

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

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

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

By estimating equation (2), the authors 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).

3.3.2 Estimating Intertemporal Relationships

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

$$LLP_{i,t} = \left[\sum_{j=1}^{2} LLP_{i,t-j} \vee \sum_{j=1}^{2} LIQ_{i,t-j}\right] + \left[\sum_{j=1}^{2} \text{X-Eff}_{i,t-j} \oplus \sum_{j=1}^{2} \pi\text{-Eff}_{i,t-j}\right] + \sum_{j=1}^{2} \text{E/TA}_{i,t-j} + \text{TA}_{\text{i,t}} + \text{ID}_{\text{i,t}} + \text{MRISK}_{\text{i,t}} + \text{YEAR}_{\text{t}} + \varepsilon_{i,t} \quad (6)$$

$$LIQ_{i,t} = \left[\sum_{j=1}^{2} LLP_{i,t-j} \vee \sum_{j=1}^{2} LIQ_{i,t-j}\right] + \left[\sum_{j=1}^{2} \text{X-Eff}_{i,t-j} \oplus \sum_{j=1}^{2} \pi\text{-Eff}_{i,t-j}\right] + \sum_{j=1}^{2} \text{E/TA}_{i,t-j} + \text{TA}_{\text{i,t}} + \text{ID}_{\text{i,t}} + \text{MRISK}_{\text{i,t}} + \text{YEAR}_{\text{t}} + \varepsilon_{i,t} \quad (7)$$

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

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

$$\mathrm{E/TA_{i,t}} = \left[\sum_{j=1}^{2} LLP_{i,t-j} \vee \sum_{j=1}^{2} LIQ_{i,t-j}\right] + \left[\sum_{j=1}^{2} \text{X-Eff}_{i,t-j} \oplus \sum_{j=1}^{2} \pi\text{-Eff}_{i,t-j}\right] + \sum_{j=1}^{2} \mathrm{E/TA}_{i,t-j} + \mathrm{TA_{i,t}} + \mathrm{ID_{i,t}} + \mathrm{MRISK_{i,t}} + \mathrm{YEAR}_t + \varepsilon_{i,t} \quad (10)$$

i and *t* are defined as before. LLP is loan loss provision scaled by total loans, LIQ is liquid assets scaled by total demand deposits, X-Eff and π-Eff are cost- and profit-efficiency measured in the first step, E/TA is equity capital scaled by total assets. In addition to these variables, the authors 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 and YEAR are year dummies.

Since the authors estimate a dynamic panel model with added lags of the dependent variable as independent variables, the estimation via OLS is problematic: Lagged dependent variables correlate with the error term due to unobserved heterogeneity, which causes upward biases of the relevant coefficients. In order to tackle this issue, the authors 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 only removed in cases when $T \rightarrow \infty$, otherwise the coefficients are downward biased. Due to this problem, Arellano and Bond (1991) developed 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 difference GMM is more appropriate, it still causes problems with estimations in micro panel data sets 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 difference GMM are weak instruments and the resulting coefficients are downward biased.

For these reasons, the authors use the two-step system GMM estimator based on Arellano and Bover (1995) and Blundell and Bond (1998).[28] System GMM extends difference GMM by adding equations in levels as potential moment restrictions. Since the resulting standard errors in system GMM are downward biased in small T panels, the authors apply the standard error correction for finite-sample panels developed by Windmeijer (2005).

The authors 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 in order to control for fixed effects. $\Delta\varepsilon_{i,t}$ should correlate with $\Delta\varepsilon_{i,t-1}$, if fixed effects were eliminated successfully, since both differences share the component $\varepsilon_{i,t-1}$. AR(2) tests for endogeneity of lags of the dependent variable. If the AR(2) test shows significance below 10%, lags of the variable are endogenous and hence bad instruments. The Hansen test for overidentifying restrictions tests the null hypothesis whether employed instruments are - as a group - exogenous, thus good instruments. Contrary to Sargan test, Hansen test is robust to heteroscedasticity and autocorrelation but too many instruments may weaken results. Since the authors use a reasonable amount of instruments, this limitation is applicable in our setting.[29]

Existing literature in this field recommends the use of two lags (e.g. Casu and Girardone, 2009; Fiordelisi, Marquez-Ibanez and Molyneux, 2011; Williams, 2004). Applying these two lags, the authors calculate the total effect of the lagged variables as the sum of their coefficients. Based on this total effect, the authors employ two different Wald-tests to check for Granger-causality. Wald-test 1 represents for each lagged variable the joint test of the null 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.[30] Wald-test 2 represents for each lagged variable the test of the null hypothesis that the sum of

[28] The authors apply the system GMM estimator by using the Stata command "xtabond2" written by Roodman, 2009.

[29] Details concerning system GMM, AR(1), AR(2) and Hansen test are in Appendix E.

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

both lags is equal to zero. If the null hypothesis in Wald 2 is not rejected, the level of the dependent variable is influenced by the change of the lagged independent variable and not by its level.

3.4 Variables, Data and Descriptive Statistics

Due to data limitations, the authors follow Williams (2004) and use loan loss provision (LLP) as a proxy for credit risk. Regarding capital, the authors use the equity-to-asset ratio (E/TA) calculated as the book value of equity to total assets. This measure clearly reflects bank capital risk. The authors further use a broader measure of bank capital as a robustness test. This alternative measure of bank capital (E_A/TA) includes funds for general bank risks, participation rights and subordinated liabilities on top of the standard measure of bank equity capital. The authors use this measure in order to gain a deeper understanding of how additional capital reserves built by banks relate to the relevant variables of investigation. For the investigation of bank liquidity risk, the authors employ a measure for bank liquidity risk (LIQ) applied by Radic´ (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 from banks and private households. Concerning our risk measures, the authors 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).

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

The authors 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 institutions and bills of exchange, bonds and other fixed-interest securities, shares and other non-fixed-interest securities). The authors consider this measure as important since our data covers the recent financial crisis, which led to substantial shifts on banks' balance sheets. The same accrues to our measure of income diversification (ID), which aims to capture differences in business focus across banks by contrasting commission margin, trade margin and other earning assets to net operating income. The natural logarithm of total assets (TA) controls for differences in bank asset size. Finally, year dummy variables are included to capture heterogeneity of the macroeconomic development across years.[31]

The authors use accounting data from 354 cooperative banks (1940 observations) from Germany between 2005 and 2010. Non-listed banks in Germany are required to publish annual accounting data in the German "Bundesanzeiger". Hence, the authors hand-collected annual balance sheet and income statement data from the German "Bundesanzeiger" (www.bundesanzeiger.de). The authors adjusted the dataset as follows: Since mergers may bias estimation results, the authors decided to drop all banks who were part of a merger. Eliminating mergers results in a sample of 258 banks (1548 observations). In order to obtain a balanced panel the authors dropped all banks with less than six observations. This results in a final sample of 253 cooperative banks and 1518 observations.

Table 3.1 Sample Selection.

	Observations
Initial sample of cooperative banks from Germany with balance sheet and income statement data from 2005 to 2010 from the German "Bundesanzeiger".	1940
Less: Banks being part of a merger between 2005 and 2010.	-392
Less: Banks with less than 6 observations.	-30
Final Sample	1518

[31] See Appendix A for detailed information concerning variable description.

Cooperative banks are retail oriented banks who differ to some extend from commercial banks in terms of e.g. the nature of non-interest income. Thus, they rather focus on commission income (fees) than on commercial paper or financial derivatives as a form of non-interest income. At the same time, cooperative banks pertain to the group of small banks such as community banks, savings banks and credit unions. These banks play an important role in many western countries (US, Australia and several countries in Europe) as they rely on relationship lending with strong focus on local development. This is what makes these banks of particular interest as their competitive environment differs largely from commercial banks.

Table 3.2 contains summary statistics of the variables of interest. While mean cost-efficiency is about 94.21% average profit-efficiency is slightly higher (95.50%). Loan loss provision ranges from -2.02% up to 3.92%, thus indicating 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 (1.77%). The equity-to-assets ratio reveals that some banks hold large shares of equity capital (maximum of 11.90%) whereas others rather hold low shares of equity capital (minimum of 2.61%). While some banks do not participate in market related investments (0.00%) others are heavily invested in these assets (58.59%). Total assets range from 21 Million Euro up to 4.6 Billion Euro, indicating that our sample comprises small and medium sized banks.[32]

Table 3.3 exhibits the development of the variables of interest over time. Liquidity dries up from over 40 percent in 2005 to less than 20 percent in 2010. The influence of the recent financial crisis is appreciable by the inverted U-shaped form of cost efficiency scores and the U-shaped profit efficiency scores.

[32] See Appendix B for correlation matrix of relevant variables.

Table 3.2 Descriptive statistics.

	Mean	Median	SD	Min	Max
X-Eff.	0.9421	0.9533	0.0389	0.7132	0.9913
π-Eff.	0.9550	0.9693	0.0461	0.0003	0.9918
LLP	0.0061	0.0058	0.0049	-0.0202	0.0392
LIQ	0.2857	0.2449	0.1791	0.0177	2.0543
E/TA	0.0601	0.0581	0.0131	0.0261	0.1190
E_A/TA	0.0666	0.0645	0.0146	0.0375	0.1500
MRISK	0.2570	0.2468	0.1087	0.0000	0.5859
TA*	319.547	211.79	391.23	21.053	4,607.324
ID	0.2697	0.2692	0.1006	-1.3254	0.6514

*in Million Euro

Thus, there is some evidence that banks were not able to hold high profit efficiency levels during the crisis but managed to improve their cost-exposure over the respective period. Similarly, the mean equity-to-assets ratio (E/TA) declined from 6.11% in 2006 to 5.92% in 2008, before it started rising again up to 6.06% in 2010. The numbers of our measure of market risk (MRISK) are particularly interesting, since they show that cooperative banks shifted their balance sheet towards these assets (especially after the period of the financial crisis). Total assets (TA) indicates that cooperative banks are growing in asset size on average. Income diversification (ID) shows that the average bank refrains from generating non-interest income (the number decreases from 35.10% in 2006 to 21.33% in 2009).

Table 3.3 Descriptive statistics of relevant regression variables over time.

	LLP	LIQ	X-Eff	π-Eff	E/TA	E_A/TA	MRISK	TA*	ID
2005	0.0059	0.4015	0.9449	0.9736	0.0593	0.0653	0.2406	289.0866	0.2606
2006	0.0094	0.3356	0.9333	0.9736	0.0611	0.0675	0.2374	295.7120	0.3510
2007	0.0060	0.2903	0.9486	0.9395	0.0610	0.0671	0.2330	308.0154	0.2987
2008	0.0057	0.2645	0.9470	0.8968	0.0592	0.0649	0.2415	326.3144	0.2564
2009	0.0044	0.2412	0.9573	0.9618	0.0596	0.0663	0.2935	343.7207	0.2380
2010	0.0053	0.1912	0.9213	0.9849	0.0606	0.0684	0.2959	354.4328	0.2133
Total	0.0061	0.2874	0.9421	0.9550	0.0601	0.0666	0.2570	319.5470	0.2697

*in Million Euro

3.5 Empirical Results

3.5.1 Cost-efficiency Estimations

Following Fiordelisi, Marquez-Ibanez and Molyneux (2011) the authors estimate credit risk (LLP), cost efficiency (X-Eff)[33] and equity capital (E/TA). In addition, the authors re-estimate these regressions by replacing loan loss provision (LLP) with liquidity (LIQ) in order to investigate all links concerning bank liquidity risk (Table 3.4, columns 4-6). Finally, the authors estimate a comprehensive bank risk model by including liquidity risk, credit risk (LLP) and capital risk (E/TA) in the same estimation (Table 3.4, columns 7-10).

Results in Table 3.4 suggest that cost efficiency negatively Granger-causes loan loss provision (the authors do not find a level-effect in model 7). Wald-test 1 is significant on the 5%-level, indicating that both periods (t-1 and t-2) separately influence loan loss provision in t. Thus, the authors confirm the "bad management" hypothesis, which indicates that low

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

cost-efficiency leads to an increasing share of problem loans. Put differently, banks can reduce the amount of problem loans by efficient monitoring and control costs. This is in line with Berger and DeYoung (1997), Kwan and Eisenbeis (1997) and Williams (2004) who find similar results.

With respect to equity capital (E/TA), our results show evidence against the "moral hazard" hypothesis. Specifically, the authors measure a positive relation between equity capital and loan loss provision, suggesting that banks with low equity 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 particular the business model of cooperative banks, which is based on the interests of its commonly local customers (the cooperative act: § 1 GenG) may reason this finding.

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

The authors also show that there is a negative relationship between loan loss provision and equity capital in column 3 and 10. This result is not surprising, since loan loss provision burns equity capital. Clearly, the authors do not find a level-effect, however both lagged values are jointly significant on the 1% and 10% level.

Results also indicate that decreases in equity capital Granger-cause increases in cost-efficiency for all three cost-efficiency estimations. That is, banks that suffer from decreasing equity capital are inclined to manage their costs in following periods. This confirms our results concerning the "moral hazard" hypothesis. Thus, cooperative banks do not suffer from inappropriate incentives when capital declines.

Moreover, the authors identify a positive impact from liquidity on equity capital in our liquidity and our comprehensive risk model (column 6 and 10). Results are significant on a

Table 3.4 Regression results for the relationship between risk, cost-efficiency and capital of sample banks using Granger-causality-technique.

	(1) Y = LLP	(2) Y = X-Eff$_t$	(3) Y = E/TA$_t$	(4) Y = LIQ	(5) Y = X-Eff$_t$	(6) Y = E/TA$_t$	(7) Y = LLP	(8) Y = LIQ	(9) Y =X-Eff$_t$	(10) Y = E/TA$_t$
LLP$_{t-1}$	-0.430**	-2.01	-0.091				-0.501***	0.910	-2.669	-0.120
	(0.180)	(1.827)	(0.092)				(0.183)	(1.384)	(1.951)	(0.086)
LLP$_{t-2}$	-0.206	-4.708***	0.088**				0.291	-1.406	-4.419**	0.095**
	(0.166)	(1.419)	(0.031)				(0.252)	(0.957)	(1.920)	(0.043)
LLP$_{Wald\ 1}$	-0.636*	-6.718***	-0.003***				-0.21***	-0.496*	-7.088*	-0.025*
LLP$_{Wald\ 2}$	-0.636**	-6.718**	-0.003				-0.21	-0.496	-7.088**	-0.025
LIQ$_{t-1}$				0.168	0.026	0.009*	0.004	0.133	-0.024	0.007
				(0.105)	(0.029)	(0.005)	(0.008)	(0.133)	(0.048)	(0.005))
LIQ$_{-2}$				0.153*	0.004	0.004*	0.007*	0.155**	-0.034	0.004*
				(0.082)	(0.010)	(0.002)	(0.004)	(0.073)	(0.023)	(0.003)
LIQ$_{Wald\ 1}$				0.321	0.030	0.013***	0.011	0.288	-0.058	0.011***
LIQ$_{Wald\ 2}$				0.321**	0.030	0.013***	0.011	0.288*	-0.058	0.011***
X-Eff$_{t-1}$	-0.029	0.276	0.004	-0.117	0.120	-0.018	-0.067**	0.024	0.363	-0.006
	(0.021)	(0.239)	(0.012)	(0.469)	(0.161)	(0.012)	(0.028)	(0.290)	(0.233)	(0.017)
X-Eff$_{t-2}$	-0.020	-0.091	0.006	-0.048	0.048	-0.000	0.066**	-0.220	0.102	0.008
	(0.020)	(0.218)	(0.006)	(0.369)	(0.071)	(0.006)	(0.027)	(0.207)	(0.205)	(0.006)
X-Eff$_{Wald\ 1}$	-0.049	0.185	0.010	-0.165	0.168	-0.018	-0.001**	0.002	0.465	0.002
X-Eff$_{Wald\ 2}$	-0.049**	0.185	0.010	-0.165	0.168	-0.018	-0.001	0.002	0.465	0.002
E/TA$_{t-1}$	-0.613**	2.000**	1.102***	-2.084	4.122**	1.035***	-0.167*	-3.612	2.029**	1.173***

	(0.313)	(0.898)	(0.136)	(5.219)	(1.620)	(0.229)	(0.093)	(6.802)	(0.883)	(0.285)
E/TA_{t-2}	0.780**	-2.628***	-0.127	2.568	-4.798***	-0.025	0.275***	4.060	-2.503***	-0.149
	(0.321)	(0.921)	(0.140)	(5.394)	(1.687)	(0.237)	(0.091)	(6.855)	(0.912)	(0.294)
$E/TA_{Wald\ 1}$	0.167**	-0.628**	0.975***	0.484	-0.676***	1.010***	0.108**	0.448	-0.474**	1.024***
$E/TA_{Wald\ 2}$	0.167**	-0.628	0.975***	0.484	-0.676*	1.010***	0.108	0.448	-0.474	1.024***
MRISK	0.013***	-0.027	-0.002	-0.266***	0.050	0.006	0.001	-0.199*	0.009	0.006
	(0.007)	(0.034)	(0.004)	(0.096)	(0.033)	(0.005)	(0.017)	(0.113)	(0.045)	(0.005)
TA	0.003	0.000	-0.000	-0.055**	0.002	0.001	0.001	-0.042**	-0.004	0.001
	(0.002)	(0.012)	(0.001)	(0.027)	(0.006)	(0.001)	(0.002)	(0.019)	(0.008)	(0.001)
ID	0.013	-0.047	-0.001	0.020	0.132***	0.000	0.007	-0.076**	-0.010	-0.001
	(0.012)	(0.101)	(0.004)	(0.160)	(0.045)	(0.005)	(0.008)	(0.032)	(0.080)	(0.003)
CONST	-0.014	0.072**	-0.009	1.364**	0.720***	0.003	-0.027	1.173**	0.629*	-0.021
	(0.040)	(0.386)	(0.015)	(0.593)	(0.222)	(0.022)	(0.042)	(0.470)	(0.363)	(0.021)
Observations	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012
Instruments	40	41	45	52	47	40	35	57	48	42
Hansen test, 2nd step	35.32	35.93	23.37	37.05	28.54	34.48	10.20	33.72	38.91	25.68
AB test AR (1)	-2.07**	-2.10**	-4.11***	-2.54**	-3.27***	-2.46**	-2.13**	-2.32**	-1.90*	-2.28**
AB test AR (2)	-0.42	-0.03	0.12	-0.37	1.68*	-0.37	-1.11	-0.62	-0.86	-0.16

The authors use two-step system GMM estimations with Windmeijer (2005) corrected standard errors. Wald 1-coefficiencts capture joint test of the null hypothesis that both lags are equal to zero and is 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 if the null hypothesis (applied instruments are not correlated with the error term) is valid. Arellano-Bond (AB) test for serial correlation tests if the null hypothesis (errors in the first difference regression do not suffer from second order serial correlation) is valid. For brevity, the authors do not report results of year-dummies in our regressions.

Table 3.5 Robustness test: Testing the relationship between risk, cost-efficiency and capital (using equity capital plus supplemental capital items to total assets as a measure for 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}	-0.370***	-0.124	-0.112				-0.353***	3.591	-0.302	-0.551
	(0.091)	(0.733)	(0.102)				(0.083)	(5.572)	(0.816)	(0.459)
LLP_{t-2}	-0.247**	-0.438	0.096				-0.194**	-1.533	-0.217	0.001
	(0.115)	(1.088)	(0.073)				(0.096)	(3.515)	(1.216)	(0.187)
$LLP_{Wald\ 1}$	-0.617***	-0.562	-0.016*				-0.547***	2.058	-0.519	-0.550
$LLP_{Wald\ 2}$	-0.617***	-0.562	-0.016				-0.547***	2.058	-0.519	-0.550
LIQ_{t-1}				0.131	-0.099**	0.002	-0.001	0.165	-0.090**	-0.006
				(0.111)	(0.046)	(0.008)	(0.004)	(0.146)	(0.039)	(0.011)
LIQ_{t-2}				0.107	-0.049*	0.001	0.001	0.117*	-0.032	0.008*
				(0.090)	(0.026)	(0.003)	(0.003)	(0.068)	(0.022)	(0.004)
$LIQ_{Wald\ 1}$				0.238	-0.148***	0.003	0.000	0.282**	-0.122***	-0.002
$LIQ_{Wald\ 2}$				0.238	-0.148***	0.003	0.000	0.282**	-0.122***	-0.002
X-Eff_{t-1}	-0.030**	0.383**	0.004	-0.182	0.557***	0.065*	-0.014	-0.411	0.470***	0.055
	(0.015)	(0.150)	(0.020)	(0.438)	(0.159)	(0.039)	(0.014)	(0.526)	(0.132)	(0.048)
X-Eff_{t-2}	-0.021*	0.183	-0.011	0.001	0.280**	0.016	-0.017	-0.082	0.245	-0.014
	(0.012)	(0.122)	(0.017)	(0.221)	(0.121)	(0.029)	(0.010)	(0.477)	(0.167)	(0.022)
X-$Eff_{Wald\ 1}$	-0.051**	0.566**	-0.007	-0.181	0.837***	0.081	-0.031	0.493	0.715***	0.031
X-$Eff_{tWald\ 2}$	-0.051***	0.566***	-0.007	-0.181	0.837***	0.081*	-0.031*	0.493	0.715***	0.031
E_A/TA_{t-1}	-0.218*	1.808***	0.990***	-2.158	1.688***	1.268***	-0.165	-1.347	1.922***	1.542***

	(0.128)	(0.603)	(0.066)	(2.974)	(0.616)	(0.317)	(0.117)	(3.979)	(0.609)	(0.402)
E_A/TA_{t-2}	0.337**	-2.144***	0.074	3.537	-2.084***	-0.254	0.240*	2.152	-2.254***	-0.559
	(0.148)	(0.649)	(0.071)	(2.945)	(0.664)	(0.322)	(0.129)	(4.163)	(0.718)	(0.416)
$E_A/TA_{Wald\ 1}$	0.119**	-0.366***	1.064***	1.379	-0.396***	1.014***	0.075	0.805	-0.332***	0.983***
$E_A/TA_{Wald\ 2}$	0.119*	-0.366	1.064***	1.379	-0.396	1.014***	0.075	0.805	-0.332	0.983***
MRISK	0.011*	-0.018	0.002	-0.199**	0.009	-0.002	0.009*	-0.117	0.011	0.006
	(0.006)	(0.025)	(0.004)	(0.082)	(0.041)	(0.010)	(0.005)	(0.154)	(0.042)	(0.010)
TA	0.002	0.009	0.001*	-0.026	-0.011	-0.000	0.000	-0.051**	-0.005	-0.000
	(0.002)	(0.006)	(0.001)	(0.021)	(0.010)	(0.001)	(0.001)	(0.024)	(0.007)	(0.001)
ID	0.017***	-0.045	-0.008*	0.143	-0.025	-0.004	0.018***	-0.057	-0.016	-0.005
	(0.003)	(0.077)	(0.005)	(0.225)	(0.073)	(0.008)	(0.003)	(0.292)	(0.071)	(0.009)
CONST	0.009	0.245	-0.022	0.738	0.393*	-0.074*	0.022	1.555**	0.398*	-0.027
	(0.035)	(0.189)	(0.020)	(0.633)	(0.235)	(0.041)	(0.028)	(0.768)	(0.215)	(0.048)
Observations	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012
Instruments	51	63	58	51	48	36	56	41	60	33
Hansen test, 2nd step	37.78	61.79	48.54	27.88	30.82	31.98	36.61	22.40	48.60	20.53
AB test AR (1)	-3.19***	-3.51***	-5.03***	-2.72***	-3.36***	-2.30**	-3.07***	-2.38**	-3.08***	-2.52**
AB test AR (2)	0.74	0.05	-0.02	-0.02	-0.32	0.53	0.14	-0.11	-0.34	0.37

The authors use two-step system GMM estimations with Windmeijer (2005) corrected standard errors. Wald 1-coefficiencts capture joint test of the null hypothesis that both lags are equal to zero and is 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 if the null hypothesis (applied instruments are not correlated with the error term) is valid. Arellano-Bond (AB) test for serial correlation tests if the null hypothesis (errors in the first difference regression do not suffer from second order serial correlation) is valid. For brevity, the authors do not report results of year-dummies in the regressions.

1% level. Thus, increases in liquidity precede increases in equity capital. As risk preferences commonly reflect the amount of both equity capital and liquidity, this finding is economically reasonable.

The authors also find evidence of a negative relationship between total assets (TA) and liquidity (columns 4 and 8). This means that large banks tend to hold less liquidity than small banks. At the same time, results show that market risk is positive related to loan loss provision. Market risk reflects managements' risk preferences, since this measure captures all market related investments (interest rate changes affect those investments immediately). Consequently, banks who have a high exposure to market risk are also inclined to take on more risk concerning their loan portfolio. The negative relation between market risk and liquidity risk also reveals those risk preferences: Banks who shift assets towards market related investments are prone to decrease liquidity. Finally, income diversification relates positively to cost-efficiency and negatively to liquidity. Thus, diversified banks tend to be more cost-efficient but hold less liquidity.

Turning to Table 3.5, the authors employ a broader measure of equity capital, E_A/TA (total capital), which adds funds for general banking risks, special items related to currency conversion, participation rights and subordinated liabilities to the book value of equity capital. While the authors can confirm the previous finding in terms of a negative relationship between loan loss provision and equity capital, the authors do not get any significant results concerning the relationship between loan loss provision and cost efficiency. This indicates that the negative relation between these two components gets blurred when total capital is employed in the regression.

Further, the authors now measure on a 1 percent level that liquidity negatively Granger-causes cost efficiency. That is, banks who hold high levels of liquidity perceive decreasing cost-efficiency in following periods. However, concerning the relation between liquidity and total capital, the authors do not get any significant results.

Similar to results in Table 3.4, the authors find some evidence (in column 1 and 7) that banks who hold high shares of market risk are also inclined to take on more risk concerning their loan portfolio, hence yielding higher loan loss provision. Finally, the authors identify little evidence (on a 10%-level) that cost-efficiency positively Granger-causes bank capital.

3.5.2 Profit-efficiency Estimations

Table 3.6 shows all regressions related to profit efficiency[34]. The authors find weak evidence (on a 10%-level) for a negative relationship between profit efficiency and loan loss provision (column 1 and 7). Thus, the authors show that the "bad management" hypothesis can also be confirmed when the authors use profit efficiency as a measure for bank efficiency. Banks who are not able to manage earnings perceive higher credit risk in following periods.

In contrast to the cost-efficiency estimations, results for credit risk estimations show only weak evidence of a positive impact of equity capital on loan loss provision. In the comprehensive risk model (column 7), the authors do not measure any significant effect concerning this relation. Results also show a negative impact from loan loss provision on profit efficiency (column 3 and 9) yielding a bi-directional relationship between these two measures. Thus, the authors can also confirm the "bad luck" hypothesis for the profit-

efficiency estimations. However, the authors do not measure any effect between equity capital and profit efficiency in any of the three model specifications. Thus, cooperative banks with low equity rather focus on managing their costs than their profits. With regard on the equity estimations, the authors find - similar to the cost-estimations - no significant effect from profit-efficiency on equity capital.

In terms of liquidity, results are rather scarce. The authors only find evidence of a positive relation between liquidity and equity capital. This fits to the results from the cost-efficiency

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

Table 3.6 Testing the relationship between 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$_{t-1}$	-0.217***	-0.701**	-0.130				-0.293**	0.032	-2.471**	-0.072*
	(0.072)	(0.356)	(0.080)				(0.134)	(1.459)	(1.047)	(0.039)
LLP$_{t-2}$	0.043	-0.888*	0.067*				0.050	-2.735	-2.284**	0.054
	(0.063)	(0.520)	(0.036)				(0.081)	(1.775)	(1.138)	(0.034)
LLP$_{Wald\ 1}$	-0.174***	-1.589	-0.063*				-0.243*	-2.703*	-4.755**	-0.018**
LLP$_{Wald\ 2}$	-0.174	-1.589*	-0.063				-0.243*	-2.703	-4.755**	-0.018
LIQ$_{t-1}$				0.120	-0.000	0.013***	0.006	0.101	-0.000	-0.001
				(0.094)	(0.018)	(0.005)	(0.004)	(0.139)	(0.029)	(0.002)
LIQ$_{t-2}$				0.136*	-0.028	0.003	0.003	0.128*	-0.020	0.002
				(0.082)	(0.020)	(0.002)	(0.003)	(0.077)	(0.028)	(0.001)
LIQ$_{Wald\ 1}$				0.256	-0.028	0.016**	0.009	0.229	-0.020	0.001
LIQ$_{Wald\ 2}$				0.256*	-0.028	0.016***	0.009	0.229	-0.020	0.001
π-Eff$_{t-1}$	-0.005	0.077	0.005	0.077	0.017	-0.004	-0.011	0.053	0.131	0.010
	(0.008)	(0.102)	(0.007)	(0.277)	(0.100)	(0.010)	(0.008)	(0.252)	(0.110)	(0.007)
π-Eff$_{t-2}$	-0.007**	-0.058	-0.003	-0.066	-0.009	-0.001	-0.006	-0.029	-0.068	-0.003
	(0.003)	(0.036)	(0.002)	(0.187)	(0.033)	(0.003)	(0.003)	(0.167)	(0.047)	(0.002)
π-Eff$_{Wald\ 1}$	-0.012*	0.019	0.002	0.011	0.008	-0.005	-0.017	0.024	0.063	0.007
π-Eff$_{Wald\ 2}$	-0.012	0.019	0.002	0.011	0.008	-0.005	-0.017*	0.024	0.063	0.007
E/TA$_{t-1}$	-0.112	0.389	1.065***	2.834	-0.442	1.171***	-0.099	-1.693	-1.665	0.995***
	(0.071)	(1.791)	(0.276)	(7.184)	(0.317)	(0.276)	(0.075)	(7.090)	(1.872)	(0.217)
E/TA$_{t-2}$	0.163**	-0.683	-0.075	-2.548	0.352	-0.179	0.147*	2.014	1.409	0.012

	(0.077)	(1.776)	(0.279)	(7.354)	(0.335)	(0.270)	(0.076)	(7.232)	(1.801)	(0.221)
$E/TA_{Wald\ 1}$	0.051*	-0.294	0.99***	0.286	-0.09	0.992***	0.048	0.321	-0.256	1.007***
$E/TA_{Wald\ 2}$	0.051	-0.294	0.99***	0.286	-0.09	0.992***	0.048	0.321	-0.256	1.007***
MRISK	0.009*	-0.014	0.006	-0.214**	-0.006	0.007	0.016***	-0.229*	-0.002	-0.005
	(0.004)	(0.029)	(0.004)	(0.094)	(0.019)	(0.005)	(0.005)	(0.119)	(0.035)	(0.003)
TA	-0.001	-0.008	0.000	-0.050***	-0.009	0.001*	-0.000	-0.048***	-0.011	-0.000
	(0.001)	(0.005)	(0.000)	(0.019)	(0.006)	(0.001)	(0.001)	(0.018)	(0.008)	(0.000)
ID	0.016***	-0.014	-0.003	-0.042	0.003	0.004	0.016*	-0.073***	0.049	-0.000
	(0.005)	(0.014)	(0.006)	(0.033)	(0.014)	(0.007)	(0.008)	(0.027)	(0.065)	(0.001)
CONST	0.024	1.146***	-0.010	1.123*	1.157***	-0.022	0.010	1.114**	1.159***	-0.002
	(0.019)	(0.188)	(0.015)	(0.596)	(0.186)	(0.018)	(0.021)	(0.536)	(0.270)	(0.015)
Observations	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012
Instruments	64	47	35	51	52	31	53	48	40	65
Hansen test, 2nd step	50,13	37.37	16.35	34.88	33,82	18.33	40.55	25.89	32.74	54.35
AB test AR (1)	-3.74***	-1.79*	-2.33**	-2.59***	-1.71*	-2.53**	-1.97**	-2.22**	-1.77*	-2.70***
AB test AR (2)	-1.69*	0.95	0.14	-0.65	0.05	-0.18	-1.70*	-0.40	0.99	0.17

The authors use two-step system GMM estimations with Windmeijer (2005) corrected standard errors. Wald 1-coefficiencts capture joint test of the null hypothesis that both lags are equal to zero and is 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 if the null hypothesis (applied instruments are not correlated with the error term) is valid. Arellano-Bond (AB) test for serial correlation tests if the null hypothesis (errors in the first difference regression do not suffer from second order serial correlation) is valid. For brevity, the authors do not report results of year-dummies in the regressions.

Table 3.7 Robustness test: Testing the relationship between risk, profit-efficiency and capital (using equity capital plus supplemental capital items to total assets as a measure for 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/Y	(9) Y = π-Eff$_t$	(10) Y = E_A/TA_t
LLP_{t-1}	-0.196***	-0.549	-0.136				0.080	2.334	-2.070	-0.237
	(0.067)	(0.365)	(0.105)				(0.180)	(2.483)	(1.379)	(0.162)
LLP_{t-2}	0.054	-0.722*	0.090*				-0.108	-0.520	-3.881**	0.226***
	(0.062)	(0.408)	(0.053)				(0.217)	(2.445)	(1.553)	(0.065)
$LLP_{Wald\ 1}$	-0.142***	-1.271	-0.046*				-0.028	1.814	-5.951**	-0.011***
$LLP_{Wald\ 2}$	-0.142	-1.271*	-0.046				-0.028	1.814	-5.951**	-0.011
LIQ_{t-1}				0.148**	-0.015	0.007*	0.013*	0.231**	0.022	-0.009
				(0.066)	(0.041)	(0.004)	(0.007)	(0.095)	(0.042)	(0.006)
LIQ_{t-2}				0.112**	-0.010	0.003	0.002	0.101*	-0.062**	-0.001
				(0.052)	(0.016)	(0.003)	(0.004)	(0.057)	(0.032)	(0.003)
$LIQ_{Wald\ 1}$				0.260***	-0.025	0.010	0.015	0.332***	-0.040	-0.010
$LIQ_{Wald\ 2}$				0.260***	-0.025	0.010*	0.015*	0.332***	-0.040	-0.010
π-Eff$_{t-1}$	-0.003	0.013	0.003	0.158	-0.021	0.004	-0.013	0.318*	0.109	-0.014
	(0.009)	(0.068)	(0.013)	(0.129)	(0.117)	(0.012)	(0.011)	(0.166)	(0.117)	(0.011)
π-Eff$_{t-2}$	-0.008**	-0.035	0.004	-0.173***	-0.243*	0.001	-0.007	-0.205***	-0.046	-0.014
	(0.003)	(0.032)	(0.010)	(0.052)	(0.139)	(0.007)	(0.005)	(0.076)	(0.066)	(0.012)
π-Eff$_{Wald\ 1}$	-0.011*	-0.022	0.007	-0.015***	-0.264	0.005	-0.020	0.113**	0.063	-0.028
π-Eff$_{Wald\ 2}$	-0.011	-0.022	0.007	-0.015	-0.264	0.005	-0.020*	0.113	0.063	-0.028
E_A/TA_{t-1}	-0.175	-0.553	1.090***	-0.908	-3.395**	1.021***	0.216	0.505	-2.898*	0.817***

	(0.175)	(0.412)	(0.314)	(1.106)	(1.441)	(0.303)	(0.330)	(1.604)	(1.583)	(0.077)
E_A/TA_{t-2}	0.279	0.376	-0.049	1.755	1.268	0.051	-0.029	0.939	1.961	0.106
	(0.192)	(0.395)	(0.350)	(1.072)	(1.640)	(0.331)	(0.285)	(1.564)	(1.668)	(0.086)
$E_A/TA_{Wald\ 1}$	0.104*	-0.177	1.041***	0.847	-2.127**	1.072***	0.187	1.444	-0.937	0.923***
$E_A/TA_{Wald\ 2}$	0.104**	-0.177	1.041***	0.847	-2.127*	1.072***	0.187	1.444*	-0.937	0.923***
MRISK	0.012***	-0.001	0.001	-0.223***	-0.091	0.000	0.020**	-0.077	-0.014	0.001
	(0.004)	(0.020)	(0.006)	(0.083)	(0.061)	(0.009)	(0.009)	(0.131)	(0.041)	(0.006)
TA	-0.001	-0.009*	0.001	-0.048***	-0.024*	0.001	0.001	-0.043***	-0.013	-0.002**
	(0.001)	(0.004)	(0.001)	(0.013)	(0.014)	(0.001)	(0.001)	(0.014)	(0.008)	(0.001)
ID	0.019***	0.026	0.001	-0.033	0.091	0.001	0.007	-0.022	0.092	-0.021*
	(0.003)	(0.041)	(0.002)	(0.028)	(0.101)	(0.002)	(0.010)	(0.173)	(0.102)	(0.011)
CONST	0.018	1.180***	-0.021	1.074***	1.841***	-0.027	-0.015	0.738*	1.263***	0.080**
	(0.023)	(0.150)	(0.021)	(0.334)	(0.505)	(0.024)	(0.031)	(0.378)	(0.296)	(0.033)
Observations	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012
Instruments	59	52	52	79	31	47	31	56	34	49
Hansen test, 2nd step	44.27	47.03	41.69	58.03	22.54	43.05	6.94	31.28	22.24	41.59
AB test AR (1)	-4.12***	-1.77*	-1.91*	-2.86***	-1.75*	-1.84*	-2.72***	-3.04***	-1.77*	-4.44***
AB test AR (2)	-1.31	0.21	0.27	-0.32	1.09	0.00	1.18	-0.21	0.52	-0.72

The authors use two-step system GMM estimations with Windmeijer (2005) corrected standard errors. Wald 1-coefficiencts capture joint test of the null hypothesis that both lags are equal to zero and is 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 if the null hypothesis (applied instruments are not correlated with the error term) is valid. Arellano-Bond (AB) test for serial correlation tests if the null hypothesis (errors in the first difference regression do not suffer from second order serial correlation) is valid. For brevity, the authors do not report results of year-dummies in the regressions.

estimations and reflects management risk preferences in both the amount of equity capital and liquidity. However, results get blurred in the comprehensive risk model (column 10).

In contrast to previous cost-efficiency estimations, the authors identify a positive impact from market risk on loan loss provision for both the model exhibiting solely loan loss provision (column 1) and for the comprehensive risk model (column 7). This confirms the view that the measure of market risk captures managements risk preferences. In addition, results for liquidity regressions (column 4 and 8) indicate that banks with a high share of market related investments are also inclined to hold less liquidity than banks with a low share of market risk. Put differently, banks controlled by a rather risk-averse management have a low share of market related investments and hence low loan loss provision but high liquidity. Finally, the results in terms of income diversification are somewhat different for the profit-efficiency estimations compared to previous cost-efficiency estimations: the authors do not measure any significant effect between income diversification and profit efficiency. However, results confirm that income diversification relates negatively to liquidity. In addition, the authors identify a positive impact from income diversification on loan loss provision. Thus, diversified banks appear to neglect the loan business in terms of adequate customer evaluation and loan monitoring.

Turning to the robustness tests (Table 3.7) results do not differ substantially. Nevertheless, there are some interesting changes: profit efficiency increases Granger-cause decreases in liquidity when total capital is used. This relation turns in the comprehensive risk model where profit efficiency relates positively to liquidity. Coefficients are similar in the cost-efficiency estimations but not significant. Moreover, the authors identify a negative relation between total capital and profit-efficiency (column 5). However, this effect is no longer significant in the comprehensive risk model (column 9). In addition, the authors find a weak (on a 10%-level) positive effect from total capital on liquidity strengthening the conclusion that banks entailing a risk-averse management tend to hold both high capital and high liquidity.

In terms of market risk, the negative relation on liquidity is no longer significant in the comprehensive risk model. At the same time, the authors identify a significant negative relation between total assets and profit efficiency (column 2 and 5) now. That is, larger banks tend to be less profit efficient than smaller banks. Finally, the authors find a weak (on a 10%-level) negative effect from income diversification on equity capital, indicating that diversified banks hold less equity.

3.6 Conclusion

The authors applied Granger-causality in order to evaluate inter-temporal relationships between capital, risk and efficiency by using contemporaneous data from German cooperative banks. Specifically, the authors evaluated whether results from current banking literature (commercial banks) also apply to a sample of cooperative banks. Thus, the authors investigated all issues between efficiency, credit- and capital risk. The authors further moved beyond current literature as the authors employed another risk measure, namely liquidity risk, to evaluate all effects concerning bank liquidity within this context. Consequently, the authors are able to develop a comprehensive risk model by including all three risk measures. At the same time, the authors use two different measures for bank efficiency, namely cost and profit efficiency, for analyzing the aforementioned inter-temporal relationships between capital, risk and efficiency. These two efficiency measures are necessary since they reflect different managerial abilities: One is the ability to manage costs and the other is to maximize profits.

Most of the results apply to current literature in this field since the authors find that lower cost and profit-efficiency Granger-cause increases in credit risk, which confirms the "bad management" hypothesis. At the same time, the authors identify that credit risk negatively Granger-causes cost and profit-efficiency ("bad luck"), hence revealing a bi-directional relationship between these measures. However, most importantly, the authors

show a positive relationship between equity and credit risk, hence displaying that moral hazard (due to limited liability and deposit insurance) does not apply to a sample of cooperative banks. This is in line with Fiordelisi et al. (2011) who identify a positive relationship between equity and non-performing loans for European commercial banks. However, contrary to Fiordelisi et al. (2011) the authors find a negative relationship between equity and cost-efficiency, indicating that struggling banks focus on managing their cost-exposure in following periods. Similar to the study from Williams (2004), the authors do not measure any effect concerning the "skimping" hypothesis. Thus, cooperative banks behave similar to savings banks, as they do not participate in skimping-behavior.

The authors showed by the study that efficiency, risk and bank capital relate inter-temporally hence revealing that bank management behavior (with regard on the results concerning the "bad management" hypothesis) may push banks closer to failure. Thus, referring to the title of this study the authors can confirm that low efficiency turns into high risk for the sample of cooperative banks.

Appendix

Appendix A

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 demand deposits)
Cost efficiency	X-Eff	X-Eff are estimated by using Stochastic Frontier Analysis
Profit efficiency	π-Eff	π-Eff are estimated by using Stochastic Frontier Analysis
Equity-to-asset ratio	E/TA	Total equity divided by total assets
Alternative Equity-to-asset ratio	E_A/TA	Calculated as: (total equity + fund for general banking risks + special items related to currency conversion + participation rights + 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)

Appendix B

Correlation matrix of relevant regression variables.

	X-Eff	π-Eff	LLP	LIQ	E/TA	E_A/TA	MRISK	TA	ID
X-Eff	1.0000								
π-Eff	-0.0036	1.0000							
LLP	-0.3570	0.0022	1.0000						
LIQ	0.0206	0.0521	0.0317	1.0000					
E/TA	-0.0426	0.0423	-0.0144	0.0923	1.0000				
E_A/TA	-0.0601	0.0645	-0.0265	0.0860	0.7823	1.0000			
MRISK	-0.0440	0.1035	0.1855	-0.1391	-0.0989	-0.0838	1.0000		
TA	0.0346	-0.1373	-0.0005	-0.3187	-0.3843	-0.3212	0.0264	1.0000	
ID	0.0258	-0.0167	0.3381	-0.0096	-0.0091	-0.0381	-0.0952	0.1016	1.0000

Appendix C

Results for 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	1.818	0.698	0.009	y2w2	λ_{22}	-0.014	0.006	0.024
y1	β_1	0.196	0.180	0.274	y2w3	λ_{23}	-0.046	0.025	0.068
y2	β_2	0.159	0.164	0.332	y3w1	λ_{31}	0.019	0.020	0.345
y3	β_3	0.648	0.133	0.000	y3w2	λ_{32}	0.013	0.006	0.019
w1	γ_1	0.354	0.178	0.047	y3w3	λ_{33}	0.009	0.020	0.658
w2	γ_2	-0.148	0.070	0.035	y1E	o_1	-0.119	0.422	0.777
w3	γ_3	0.794	0.197	0.000	y2E	o_2	0.420	0.411	0.307
E	η_1	-6.121	4.184	0.143	y3E	o_3	-0.373	0.289	0.197
T	θ_1	0.033	0.038	0.376	y1T	ρ_1	-0.004	0.004	0.302
y11	β_{11}	0.064	0.029	0.027	y2T	ρ_2	0.005	0.003	0.176
y12	β_{12}	-0.153	0.044	0.001	y3T	ρ_3	0.000	0.003	0.901
y13	β_{13}	0.005	0.031	0.883	w1E	τ_1	-0.015	0.566	0.979
y22	β_{22}	0.288	0.022	0.000	w2E	τ_2	0.059	0.155	0.705
y23	β_{23}	-0.400	0.027	0.000	w3E	τ_3	-0.794	0.598	0.184
y33	β_{33}	0.195	0.010	0.000	w1T	φ_1	0.004	0.005	0.443
w11	γ_{11}	0.210	0.035	0.000	w2T	φ_2	-0.001	0.001	0.671

w12	γ_{12}	-0.044	0.020	0.029	w3T	φ_3	0.001	0.007	0.912
w13	γ_{13}	-0.445	0.055	0.000					
w22	γ_{22}	-0.004	0.004	0.398	μ_u				
w23	γ_{23}	-0.020	0.022	0.362	cons	ψ_0	-0.011	0.076	0.885
w33	γ_{33}	0.302	0.055	0.000	INT	ψ_1	-213.387	0.955	0.025
E^2	η_{11}	42.317	12.189	0.001	ΔGDP	ψ_2	1.359	0.544	0.013
T^2	θ_{11}	-0.014	0.003	0.000					
y1w1	λ_{11}	-0.046	0.027	0.087					
y1w2	λ_{12}	0.005	0.007	0.506	σ_u		0.093	0.017	0.000
y1w3	λ_{13}	0.028	0.029	0.332	σ_v		0.034	0.004	0.000
y2w1	λ_{21}	0.033	0.021	0.117	$\lambda = (\sigma_u/\sigma_v)$		2.685	0.015	0.000

See section 3.3.1 for details about applied cost-efficiency estimation.

Appendix D

Results for 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	43.882	1.577	0.000	y2w2	λ_{22}	-0.014	0.015	0.337
y1	β_1	2.442	0.392	0.000	y2w3	λ_{23}	-0.191	0.060	0.001
y2	β_2	-3.826	0.372	0.000	y3w1	λ_{31}	0.036	0.043	0.412
y3	β_3	-1.446	0.299	0.000	y3w2	λ_{32}	-0.009	0.013	0.464
w1	γ_1	0.124	0.399	0.757	y3w3	λ_{33}	-0.142	0.044	0.001
w2	γ_2	-0.112	0.163	0.490	y1E	o_1	0.199	0.986	0.840
w3	γ_3	0.989	0.430	0.021	y2E	o_2	3.273	0.970	0.001
E	η_1	-52.072	9.534	0.000	y3E	o_3	-0.339	0.648	0.601
T	θ_1	-0.502	0.076	0.000	y1T	ρ_1	0.009	0.008	0.263
y11	β_{11}	0.134	0.068	0.048	y2T	ρ_2	0.000	0.007	0.985
y12	β_{12}	-0.289	0.104	0.005	y3T	ρ_3	-0.002	0.006	0.669
y13	β_{13}	-0.077	0.072	0.286	w1E	τ_1	-2.661	1.279	0.037
y22	β_{22}	0.238	0.052	0.000	w2E	τ_2	-0.188	0.362	0.603
y23	β_{23}	0.101	0.061	0.098	w3E	τ_3	1.328	1.349	0.325
y33	β_{33}	0.049	0.025	0.053	w1T	φ_1	-0.062	0.011	0.000
w11	γ_{11}	0.032	0.079	0.682	w2T	φ_2	-0.020	0.003	0.000

w12	γ_{12}	-0.148	0.047	0.002	w3T	φ_3	-0.041	0.016	0.009
w13	γ_{13}	0.034	0.133	0.797					
w22	γ_{22}	-0.015	0.010	0.141	μ_u				
w23	γ_{23}	-0.150	0.050	0.003	cons	ψ_0	-70960.17	5468.847	0.000
w33	γ_{33}	0.246	0.126	0.050	INT	ψ_1	1745762.0	139475.4	0.000
E^2	η_{11}	-99.576	28.605	0.000	ΔGDP	ψ_2	-392960.8	63773.36	0.000
T^2	θ_{11}	-0.017	0.004	0.000					
y1w1	λ_{11}	0.050	0.061	0.411					
y1w2	λ_{12}	-0.001	0.017	0.938	σ_u		32.460	3.671	0.000
y1w3	λ_{13}	0.343	0.064	0.000	σ_v		0.121	0.003	0.000
y2w1	λ_{21}	-0.070	0.050	0.159	$\lambda = (\sigma_u/\sigma_v)$		268.345	3.673	0.000

See section 3.3.1 for details about applied profit-efficiency estimation.

Appendix E

The authors consider the following model to clarify the GMM approach:

$$y_{i,t} = x_{i,t}\beta_1 + w_{i,t}\beta_2 + u_{i,t}$$

$$u_{i,t} = v_i + e_{i,t}$$

$\boldsymbol{x_{i,t}}$ is a vector of exogenous variables, $\boldsymbol{w_{i,t}}$ is a vector of predetermined (correlation with past error terms) and endogenous (correlation with present and past errors) variables, $\boldsymbol{u_{i,t}}$ is the error term with its components v_i (fixed effect) and $\boldsymbol{e_{i,t}}$ (random error). $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ are vectors of yet unknown parameters to estimate.

Difference GMM

Difference GMM uses the first-differenced equation to eliminate v_i and therefore potential correlation between endogenous variables and the fixed effects term. Since predetermined variables may correlate with past error terms, these variables become endogenous in differences as $\Delta w_{i,t}$ is correlated with $\Delta e_{i,t}$ ($\Delta w_{i,t} = w_{i,t} - w_{i,t-1}, \Delta e_{i,t} = e_{i,t} - e_{i,t-1}$ and $w_{i,t}$ correlates with $e_{i,t-1}$). To prevent this correlation, Arellano and Bond (1991) developed (based on Holtz-Eakin et al., 1988) the difference GMM estimator, which uses all available lags in levels of all not exogenous differenced variables (e.g. $w_{i,2}$, $w_{i,1}$and $w_{i,0}$as instruments for $\Delta w_{i,4}$).

System GMM

In difference GMM, lagged levels are bad instruments for first differences if they are highly volatile and follow a random walk. Therefore, Arellano and Bover (1995) proposed to add the original equation in levels in the equation system and instrument these with appropriate lags of their first differences (e.g. $\Delta w_{i,2}$as instrument for $w_{t,3}$).

Arellano-Bond tests for autocorrelation

The first Arellano-Bond test for autocorrelation (AR(1)) is employed to examine differenced residuals in order to eliminate unobserved fixed effects. If fixed effects are eliminated due to first differenced equation, $\Delta e_{i,t}$ should correlate with $\Delta e_{i,t-1}$, since both share the term $e_{i,t-1}$. If differences correlate, fixed effects were eliminated successfully. Otherwise the error term does still partly consist of fixed effects, which weakens the correlation. The second Arellano-Bond test for autocorrelation (AR(2)) controls for autocorrelation over two periods in differences in order to check for autocorrelation over one period in levels. Accordingly, AR(2) examines the correlation between $\Delta e_{i,t}$ and $\Delta e_{i,t-2}$ to check for correlation between $e_{i,t-1}$ and $e_{i,t-2}$. If autocorrelation exists, lags of not exogenous variables are endogenous, hence bad instruments. For example, if AR(2) exists, $y_{i,t-2}$ correlates with $e_{i,t-2}$, which correlates with $\Delta e_{i,t-2}$ and thus correlates with $\Delta e_{i,t-2}$.

Sargan and Hansen tests

The Sargan and Hansen tests are two tests for over-identifying restrictions, which check whether the instruments as a group become apparent to be exogenous, and thus are good instruments. The Sargan test is not robust to autocorrelation and heteroscedasticity, but not weakened by the number of instruments. Contrary, Hansen test is robust but gets weaker as the number of instruments increases.

Finite-sample correction for standard errors by Windmeijer (2005)

Difference and system GMM estimators both offer one- and two-step variants, with two-step being asymptotically more efficient. However, standard errors estimated by two-step estimation tend to be downward biased. To account for this issue, Windmeijer (2005) developed a finite-sample correction for the two-step covariance matrix. As a result, two-step robust system GMM is more efficient as one-step approach.

4 Financial experts on the board and bank performance: Evidence from cooperative banks

Abstract

This study refers to the study of Minton et al. (2014) who investigated US listed banks. The authors find that financial experts on the board promote pro-cyclical bank performance. However, Minton et al. (2014) do not examine whether their findings arise due to the shareholder-proximity or rather due to the risk-taking attitude of financial experts. For this reason, this study aims to contribute to identify the channels for pro-cyclical bank performance by using a sample of non-listed (cooperative) banks. Results show that financial experts on the board of cooperative banks do not promote pro-cyclical bank performance. Contrary, results show evidence that financial experts on the board of cooperative banks appear to foster long-term bank stability. This finding supports the assertion that the relation between financial experts and bank performance depends on the ownership structure. This outcome may be important for regulators, who should consider this issue when imposing new regulatory constraints concerning financial experts on bank boards. Similarly, results may be relevant for banks with a similar business model (e.g. community banks, savings banks, credit unions) who may aim to adjust their board structure in order to improve bank performance.

JEL Classification: G20, G21, G32, G01

Key Words: Corporate Governance, Financial Experts, Bank Performance, Financial Crisis, Risk Taking

4.1 Introduction

The financial crisis of 2007/08 led to huge distortions in the banking market. The failure of Lehman Brothers was the beginning of government interventions in various countries all over the world in order to prevent domestic economies from even further disruptions. In the aftermath of the crisis, politicians and regulators identified governance deficiencies as one major factor that contributed to the crisis. Besides existing studies in the banking literature (e.g. Beltratti and Stulz, 2012; Diamond and Rajan, 2009; Erkens et al., 2012) an OECD study from 2009 supports this notion (Kirkpatrick, 2009). Public debates increased awareness for the need of appropriate governance mechanisms at that time. Consequently, politicians and regulators called for more financial expertise on bank boards. Accordingly, the Basel Committee on Banking Supervision states in principle 2 that "board members should remain qualified, individually and collectively, for their positions. They should understand their oversight and corporate governance role and be able to exercise sound, objective judgement about the affairs of the bank." (BCBS, 2015). Taking these perceptions into consideration the prevailing question is whether financial experts on bank boards do really foster bank stability?

This paper aims to investigate this question by referring to the following conclusion of the study from Minton et al. (2014, p. 377):

"The results could be explained by the fact that independent financial experts, with a fiduciary duty to shareholders, understand the residual nature of the equity claims and will generally favor more risk taking. Another plausible explanation could be that external financial experts are more willing to let their bank participate in more risk-taking activities due to their familiarity with and understanding of complex financial instruments."

In their study, the authors investigate US commercial bank holding companies between the period 2003 and 2008. In particular, the authors investigate the pre-crisis

years 2003 to 2006 which they refer as “normal times”, and the years of the financial crisis 2007 – 2008. They find that financial experts on the board of banks lead to greater risk exposure in normal times (2003 – 2006). Higher risk exposure featured higher returns but has not been panelized in that period. However, the authors measure that these banks exhibit lower performance during the crisis. Thus, their results indicate that financial experts on the board of banks facilitated investment policies that foster bank performance in normal times at the cost of poor performance during the crisis. Accordingly, the authors question regulators view of more financial experts on the board leading to more banking stability. However, the authors do not examine whether their findings accrue due to financial experts who act in the interests of shareholders or due to the issue that financial experts may have a more risk-taking attitude (due to a better understanding of financial instruments) than other board members.

In a listed bank context, public asset trading provides valuable information to board members since declining stock prices commonly alert supervisors to challenge managements’ investment policies (Hau and Thum, 2009). Thus, the monitoring function shareholders provide are beneficial for banks. This is in particular important in the banking context, since banking opacity and complexity makes it difficult for customers to provide effective monitoring and to impose market discipline. In addition, deposit insurance and too-big-to-fail guarantees may even weaken monitoring incentives for customers (Acharya et al., 2009).

However, general perception is that shareholders favor more risky investments due to limited liability: They benefit from higher returns but do not bear the social costs of bank failures (Erkens et al., 2012). Similarly, capital requirements imply higher costs for banks and hence reduce returns for shareholders. Consequently, shareholders tend to favor greater risk taking in order to compensate additional costs (Laeven and Levine, 2009). If the bank management does not comply with this notion shareholders may shift their shares to other firms in order to keep their rate of return. This in turn may negatively affect a banks’ stock price and hence lead to additional (funding) costs for the bank. The literature commonly refers these associations as “shareholder pressure” that enables bank management and supervisory board to act in the interest of shareholders. One factor that

strengthens this linkage is that shareholders are able to diversify their portfolio and hence may favor even more risk. Erkens et al. (2012), Ellul and Yeramilli (2010) and Laeven and Levine (2009) find by their investigation of banks that banks with higher institutional ownership performed worse during the crisis than others: the more power arises from a single shareholder the more pro-cyclical appears to be bank performance. Accordingly, Laeven and Levine (2009) state that managers tend to be less inclined to risk than shareholders since they hold firm-specific human capital and private benefits of control. This finding supports the perception that shareholders commonly favor more risky investments than the bank management itself.

Thus, the literature views shareholders as an important part for the functioning, efficiency and soundness of the banking business, but with its weaknesses of pro-cyclical bank performance.

The key question concerning this context is whether the findings from the study of Minton et al. (2014) accrue due to the fact that financial experts' investment policies were based on the risk-taking interests of shareholders or on the perception that financial experts are more risk-taking itself (due to more financial knowledge) compared to other board members. In either way, the authors argue that financial experts on the board chose investment policies that they believed would be profitable but turned out to perform poor during the crisis. In summary, the authors address pro-cyclical bank performance to the investment policies of financial experts on board of banks but do not examine the underlying reason for this finding. In other words, the authors cannot assure whether the negative relationship between financial experts on the board and bank performance during the crisis arises due to their shareholder-proximity or due to their risk-taking attitude.

Nevertheless, why is it so important to identify the channels for this negative relationship? Supposed that this negative relationship exists due to supervisors who act in the interests of shareholders, then, financial experts on the board of banks where short-term shareholder interests play no role (e.g. savings banks, community banks, credit unions or cooperative banks) may prove beneficial with regard on bank performance during the crisis as well as in normal times. This would mean that they use their skills and

expertise to contribute sustainable growth to the bank. This possible outcome may be in particular relevant for regulators who may consider these issues when introducing new regulatory constraints according to financial experts on bank boards. At the same time, such an outcome could be beneficial for the aforementioned types of banks since results may enable them to adjust their board structure in order to improve bank performance. For this reason, this study investigates how financial experts affect bank performance by using a sample of cooperative banks.

However, ex ante, the relationship between financial experts on the board of cooperative banks and bank performance is not clear: since the crisis was an unexpected event, financial experts on the board may have supported investment policies (due to their financial knowledge) in the pre-crisis period that they thought would pay off but turned out to perform poorly during the crisis. Similarly, in the post-crisis period (2010 – 2011), better financial market knowledge and investment skills may again led financial experts return to increase risk by shifting assets in order to improve profitability. In particular their financial knowledge may enable them to do so since they may feel able (independent of the lessons learned by the crisis) to recognize risks early and hence undertake appropriate actions if necessary. This scenario would not be surprising, since various articles (e.g. Duchin and Sosyura, 2014) report that banks turned back into risky activities very quickly after the crisis in order to strive for returns. Even if this may not apply to the average cooperative bank there may exist a positive relation between financial experts on the board and bank risk. In addition, deposit insurance (provided by the cooperative banking association) may enable them to push management into riskier investment policies. However, why should financial experts on the board of cooperative banks strive for returns at a cost of higher risk? What is their benefit? A potential explanation might be that they perceive private benefits by outperforming their peers (e.g. other cooperative banks and savings banks). Furthermore, they may strive for good performance results of "their" bank in order to boost their career in the banking sector. Hence, they may use their financial knowledge to propose risky investment policies, which other board members can hardly assess.

However, financial experts may also have better financial market knowledge and better risk-management skills, which they may use in order to prevent the bank from (future) losses. Thus, it is an empirical question whether financial experts on the board of cooperative banks contribute to bank stability or not.

Taken together, this paper aims to investigate the following research question: Do financial experts on the board promote pro-cyclical bank performance in a setting where short-term shareholder interests play no role?

In order to investigate this research question, the author uses a sample of 246 cooperative banks from Germany during the period of 2006 to 2011. Cooperative banks are retail oriented banks who differ to some extend from commercial banks in terms of e.g. their nature of non-interest income. They rather focus on commission income (fees) than on commercial paper or financial derivatives as a form of non-interest income. However, their major business is to provide loans to private households and firms within their region. Their primary goal is to provide long-term lending services to their customers and to be the closest partner when it comes to financing issues. Cooperative banks pertain to the group of non-listed banks such as community banks, savings banks and credit unions. These banks play an important role in many developed countries as they provide relationship lending with focus on local development. These banks are particularly suitable to investigate the financial expert - bank performance linkage, as short-term shareholder interests play no role for these banks: equity holders are commonly customers from the region with long-term perspectives.

Thus, if this study reveals pro-cyclical bank performance related to financial experts on the board this finding arises due to the risk-taking attitude of financial experts and not due to shareholder pressure. This paper investigates the board structure – bank performance linkage during two periods: the crisis period of 2007 – 2008 and the post-crisis period of 2010 – 2011. The period of 2010 – 2011 can be marked as "normal times" on the banking market.[35]

[35] The author does not consider the year of 2009 in this context, since it is rather a "year of transition" from the crisis period (2007 – 2008) to the non-crisis period (2010 – 2011).

The author relates financial experts on the board of cooperative banks to various accounting return and risk measures. Specifically, the author uses return on equity (ROE), return on assets (ROA) and the net interest margin (NIM) as measures for bank returns. In order to address the link of financial experts to bank risk, the author uses loan loss provision (LLP), equity capital (EQUITY) and a liquidity ratio (LIQ). In the robustness section, the author employs another risk measure (MRISK) to verify the linkage of financial experts to bank risk.

In addition, the author runs the analysis by investigating two further bank board characteristics: first, the author develops a measure for occupational diversity (DIV) in order to assess whether, at which time and for which bank a diversified board proves beneficial. Second, since board size is one of the most controversial characteristics in bank governance research, the author also analyzes whether board size fosters bank performance of cooperative banks.

Large banks are commonly better diversified than small banks. As a result, large banks may be less vulnerable to economic disruptions and hence tend to take more risk than small banks. This may affect the board structure - bank performance linkage, especially during the crisis period (Cornett et al., 2010; Aebi et al., 2012; Minton et al., 2014). Thus, this study addresses this issue by running further analyses of subsamples of large and small banks. This procedure is beneficial to show that it is important to run additional analyses for subsamples as well, since board structure varies largely by bank size. Finally, the author performs various robustness tests to verify the validity of the results.

In order to analyze the research question, it is necessary to get first a better understanding of how cooperative banks performed during and after the crisis: Figure 4.1 shows the development of the (mean) return on equity (ROE) over the period 2006 to 2011. The figure shows that the crisis had a negative impact on the average return on equity of cooperative banks in 2007 and 2008. However, notably is also the return to high profitability at the year of 2009 (mean ROE of 5.73%). One might assume that this increase happened due to a lower equity ratio through the crisis. However, the average decrease of the equity-to-asset ratio during the crisis (Figure 4.5) arose through total asset

growth. In fact, average total equity rose slightly (in an unreported test the data shows an increase in the (average) absolute value of total equity). Thus, asset growth causes the declining equity-to-assets ratio from 6.08% in 2006 to 5.94% in 2009. Consequently, the increase in ROE in 2009 indicates a quick return to profitability for the average bank. Figure 4.2 shows the development of return on assets (ROA) and hence confirms this notion. In line with this finding, Figure 4.3 shows the development of the average net interest margin (NIM): In 2009, the average net interest margin was even slightly higher than in 2006. At the same time, the figure reveals that declining margins were the main reason for worse bank performance during the crisis.

Interestingly Figure 4.5 shows that loan loss provision decreases steadily over the whole period 2006 to 2011. This confirms the view that the crisis hit cooperative banks rather through higher interest expenses than through high depreciations in the credit and money market business. The author cross-checked this explanation and found that interest expenses indeed rose dramatically through the crisis. This is reasonable since banks charged higher rates for interbank - lending due to increased mistrust on the banking

Figure 4.1 Development of the (mean) return on equity (ROE) over the period 2006 to 2011.

Figure 4.2 Development of the (mean) return on assets (ROA) over the period 2006 to 2011.

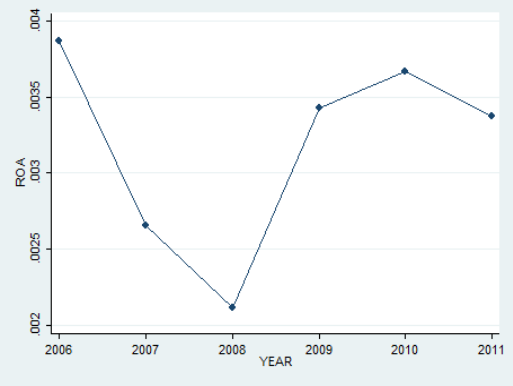


Figure 4.3 Development of the (mean) net interest margin over the period 2006 to 2011.

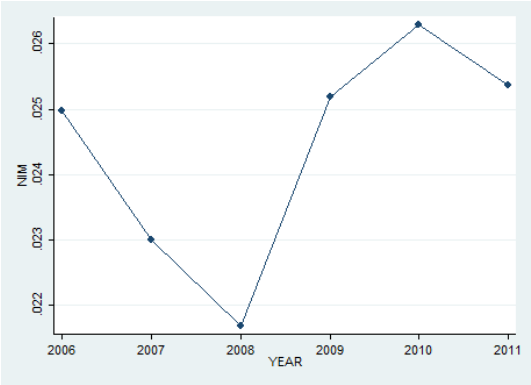


Figure 4.5 Development of the (mean) equity-to-assets ratio over the period 2006 to 2011.

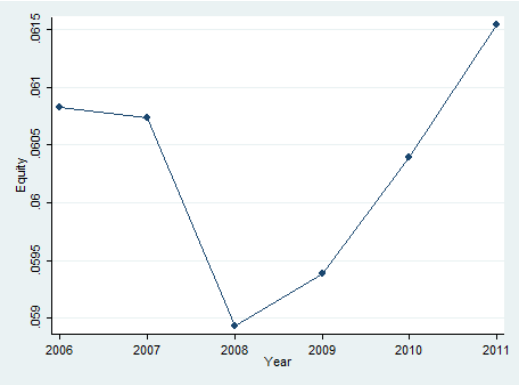
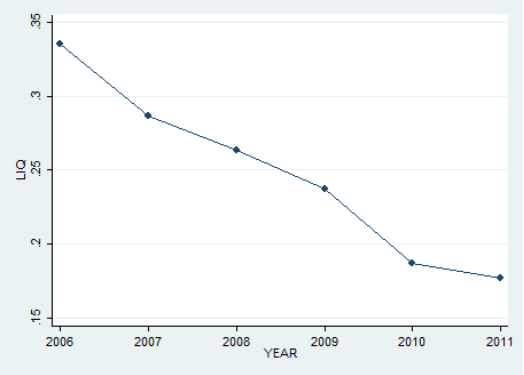


Figure 4.4 Development of the (mean) loan loss provision (LLP) over the period 2006 to 2011.

Figure 4.6 Development of the (mean) liquidity-ratio (LIQ) over the period 2006 to 2011.



market during that period.[36]

Considering the post crisis period of 2010/11 all figures provide evidence of improved bank performance except Figure 4.6: cooperative banks tend to hold less liquidity, which may be a measure to tackle phases of low interest rates since holding liquidity is costly. This measure clearly exposes cooperative banks to a higher level of liquidity risk. Nevertheless, since these figures show solely average bank performance

[36] Additional figures concerning the development of total equity, interest income and expenses are in Appendix C.

over the respective period there might be large variation in bank performance within the sample. These variations may be related to certain board structure characteristics (e.g. financial experts, occupational diversity, board size). Finally, the figures reason the approach for the definition of the crisis period (2007 – 2008) and the post-crisis period (2010 – 2011) since the year of 2009 appears as a year of transition from the crisis back to profitability. Considering the year of 2009 to either the crisis period or post-crisis period may - in turn - bias results. For this reason, the author chose not to consider the year of 2009 in the empirical analysis.

There are also studies of non-banks addressing the link of board structure and firm performance during the crisis period in the literature. However, the transfer of results from non-banks to banks does not apply due to following reasons: due to the unique role of banks for an economy and due to the complexity and opacity of the banking business (high information asymmetries to outsiders), board composition is highly specific for these entities. Business can shift very quickly compared to non-financial firms, which increases requirements for effective oversight. Hau and Thum (2009) state that differences in capital structure (high leverage) and the role of the maturity transformation processes expose banks to a higher level of liquidity risk compared to non-banks. Non-financial firms use leverage as a sthece of funding, whereas in banks leverage is a part of the production process (Mehran et al., 2011). Moreover, their strong economic ties towards multiple private borrowers as well as firms through the lending process may erupt large economic losses on a macroeconomic level (systemic risk). For this reason, regulatory constraints concerning board composition are stricter for banks than for non-banks and hence may hinder a bank to implement the optimal board structure (BCBS, 2015; Hermalin and Weisbach, 2003). Further studies exist who pronounce the importance to differentiate between banks and non-banks when analyzing board-structure – bank performance linkages (Adams and Mehran, 2003; Macey and O'Hara, 2003).

Results show that financial experts on the board of cooperative banks do not promote pro-cyclical bank performance. Contrary, results show evidence that financial experts on the board of large cooperative banks appear to foster long-term bank stability.

Since board size appears to have positive as well as negative effects for large banks during the crisis it appears to have solely positive effects (higher EQUITY and higher NIM) for small banks during that period. These diverging results may relate to differences in board size between these two subsamples: Large banks tend to have larger boards hence increasing board size for these banks may lead to less efficient decision-making processes. Contrary, small banks tend to have smaller boards hence increasing board size appears to be beneficial for those banks. In this case, adding new members to the board may provide additional knowledge and further perspectives to the board, which appears to remain still small enough to keep effective decision-making processes. Furthermore, the relation between board size and bank performance worsens for large banks in normal times. This may indicate that especially large banks should decrease board size in order to strengthen their monitoring and advising effectiveness.

Similarly, occupational diversity on the board decreases returns for large banks and decreases liquidity for small banks during the crisis. The negative impact on returns of large banks remains constant in the post-crisis period. Thus, it seems that occupational diversity of bank boards is detrimental for large banks at any time. Since the boards of large banks incorporate on average a higher diversity, this may indicate that there are limits of beneficial effects concerning occupational diversity. In addition, complexity and opacity of large banks may contribute to this finding. Finally, the results reported in this study are robust to various robustness tests.

This paper adds to the literature in several ways: first, by using a sample of non-listed (cooperative) banks this paper shows that financial experts contribute to long-term bank stability in a setting where short-term shareholder interests play no role. Thus, results from this study also add to the discussion of the results from Minton et al. (2014), by showing that their results do not apply to cooperative banks. Second, as far as the author knows, no study exists that investigated occupational diversity on the board of banks. Third, this study shows why it is important to further subdivide the sample when running an analysis of the board structure – bank performance linkage. Ftheth, by doing so, this study provides precise information how to adjust board size for small banks

(increase is beneficial) as well as for large banks (decrease is beneficial) in order to improve the monitoring and advising functions of their boards.

The paper proceeds as follows: Section 4.2 reviews relevant literature and postulates hypotheses. Section 4.3 describes the data and empirical research method. Descriptive statistics are in section 4.4 before running the empirical analysis in section 4.5. Section 4.6 shows various robustness tests and section 4.7 concludes.

4.2 Literature and Hypotheses

4.2.1 Financial Experts

Fahlenbrach and Stulz (2011) analyze 98 US financial institutions with regard on how governance structures in banks relate to performance during the financial crisis. They do not find evidence that CEOs who were less inclined to act in the interest of shareholders (measured by the dollar value of their shares) performed worse during the crisis. Contrary, they measure that banks whose CEOs hold higher stakes of the bank performed significantly worse during the crisis than banks whose CEOs hold lower shares. They argue that CEOs with better incentives to follow shareholder interests took higher risks. In the pre-crisis period, these risks have not been panelized by the market. However, these risks became (unexpectedly) prevalent during the crisis and led to poorer performance. In summary, the authors find evidence of CEOs promoting pro-cyclical bank performance the more their interests comply with those of the shareholders.

Beltratti and Stulz (2012) investigate a global sample of 387 banks with assets greater than 10 billion US-Dollar during the crisis period. They find that banks with more shareholder-friendly boards performed worse during the crisis. They identify a negative relationship between pre-crisis performance and crisis performance, hence suggesting that banks who performed better in the pre-crisis period suffered most during the crisis. Thus, they state that “banks that were pushed by their boards to maximize shareholder wealth before the crisis took risks that were understood to create shareholder wealth, but

were costly ex post because of outcomes that were not expected when the risks were taken".

Erkens et al. (2012) analyze an international sample of 296 financial firms during the financial crisis 2007/08. Their main finding is that firms with higher institutional ownership and more independent boards relate negatively to stock returns during the crisis period. Similar to Beltratti and Stulz (2012) they explain their results by firms with higher institutional ownership performed more risky investments in the pre-crisis period, which led to larger losses for shareholders during the crisis period.

Contrary to these studies Cornett et al. (2010) find for a sample of 300 publicly traded US banks that better corporate governance (higher insider ownership, more board members that are independent) relate to better performance during the crisis period.

Literature exhibits two studies who investigate how financial experts on the bank board affect bank performance: Aebi et al. (2012) investigate how various governance structure variables affect bank performance for US banks during the crisis. According to the standard governance variables (CEO ownership, board independence), they confirm the negative relationship to bank performance from Beltratti and Stulz (2012) and Fahlenbrach and Stulz (2011). Hence, they explain their findings similar by stating, "Banks were pushed by their boards to maximize shareholder wealth before the crisis and took risks that were understood to create wealth but later turned out poorly in the credit crisis". However, most importantly, they also identify a negative relationship between financial experts on the board and stock performance during the crisis. Thus, they challenge the widespread view of more financial experts on the board to be beneficial for bank performance. The authors perform various robustness tests concerning this finding and state that results remain "very similar". Subsequently, they refer to (an earlier version of) the study mentioned at the beginning of this paper of Minton et al. (2014), who find similar results. Minton et al. (2014) investigate US commercial bank holding companies between the period 2003 and 2008. They find that financial experts on the bank board lead to greater risk exposure at the onset of the financial crisis. Higher risk exposure featured higher returns but has not been panelized in the pre-crisis period. However, the authors measure that banks with these higher risk-profiles (and hence with more financial

experts on the board) are related to lower performance during the crisis. Thus, their results indicate that financial experts on bank boards facilitated investment policies that led to higher bank performance in normal times at the cost of poor performance during the crisis.

Since the authors do not examine, whether their results arise due to financial experts who act in the interests of shareholders or on the perception that financial experts are more risk-taking itself, this study provides an interesting setup to do so: Since short-term interests of shareholders play no role for cooperative banks, outcomes could be solely addressed to the risk-taking attitude and skills of financial experts on the board.

Financial experts on the board surely exhibit lower costs in the acquisition and evaluation of investment related information and hence are more efficient in monitoring management (Harris and Raviv, 2008). Thus, financial experts are better able to identify risks that may be detrimental for the bank in the future. Contrary, they may also be more inclined to take risks since they feel more confident to assess those risks (due to their risk-taking attitude). Thus, financial experts on the board of cooperative banks may have favored more risky investments compared to other board members in the pre-crisis period. These investments may have turned out to perform poorly in the following crisis period. However, financial experts do also exhibit better risk-management skills and investment related knowledge that could be beneficial in the crisis period. For example, financial experts may be better able to prevent banks from increases in loan loss provision since they are more sensitive to detect those risks in early stages. This may enable them, in turn, to develop effective measures to prevent losses. Similarly, they exhibit greater financial market knowledge and hence may be better capable to shift securities and other commercial papers in order to keep returns up.

Concerning returns, the author assumes (according to existing literature) that financial experts may have shifted investments to more risky assets in the pre-crisis period, which may negatively influence bank returns during the crisis period. However, in the post-crisis period financial market knowledge may prove beneficial for financial experts in order to undertake actions to increase returns. Thus, the author postulates the following hypothesis:

H1: Financial experts promote pro-cyclical bank returns.

In the crisis period, the author expects increases in risk exposure are positively related to financial experts on the board since literature suggests that financial experts took risks in the pre-crisis period that have been penalized during the crisis period. In the post-crisis period, literature suggests that financial experts increase performance at a cost of slightly higher risk. Hence, the author formulates the risk-hypothesis as:

H2: Financial experts lead to higher bank risk.

4.2.2 Occupational Diversity

As far as the author knows, there is no study of occupational diversity in the banking literature. For this reason the author refers to the non-finance literature (which may face the issue mentioned at the beginning of the paper that results may not be fully transferrable to banks) which views multiple dimensions of board diversity. Ingley and Van der Valt (2003) note that "the concept of diversity relates to board composition and the varied combination of attributes, characteristics and expertise contributed by individual board members in relation to board process and decision making". Hutchinson et al. (2014) suggest that if the purpose of a board is to protect the interests of is stakeholders, then members that represent those stakeholders should compile a board. Thus, board diversity should display the connection of a firm to its external environment (Ruigrok et al, 2006a).

There are several reasons for and against diversity for boards in the literature: Hutchinson et al. (2014) and Carpenter and Westphal (2001) suggest that a higher degree of diversity may lead to improved decision-making processes in firms, since different perspectives from members with dispersed backgrounds may generate more ideas and alternatives. Similarly, Van Ness et al. (2010) examine occupational diversity from board members of S&P 500 firms. The authors find that occupational diversity increases revenue growth. They argue that firms with occupational diverse boards benefit from different perspectives (various ideas) from board members by identifying more growth-

opportunities. Moreover, a higher degree of diversity increases the knowledge base and creativity, hence strengthens the innovativeness (products and processes) of a firm (Hutchinson et al., 2014; Milliken and Martins, 1996). In fact, occupational diversity may also enable boards to fulfill any boundary-spanning role that might appear as well as improved access to restheces and information outside the firm (Ruigrok et al., 2006b).

Contrary to this notion, occupational diversity may hamper behavioral integration and hence facilitate interaction difficulties, which may turn into a lower level of action taking. Hambrick et al. (1996) find that heterogeneous groups may weaken the board consensus since heterogeneity leads to more disagreement between members. One potential explanation might be that in order to draw important decisions within a certain business board members may need a common basis of knowledge to facilitate a constructive discussion. Regarding this issue, the degree of common knowledge required may depend on the specificity of the underlying business.

Even if there is, as far as the author knows, no study of occupational diversity of board members in the banking literature, several aspects of board diversity have yet been examined: For example, Garcia-Meca et al. (2015) investigate a sample of 159 banks in nine countries from 2004 to 2010 in terms of national diversity. They assume that directors from different countries might increase heterogeneity of ideas and perspectives and hence increase performance. However, their results show a negative relationship between national diversity and bank performance. They state, "Foreign directors may face strong domestic networks and may also enctheage managers to increase shareholder returns through greater risk-taking because they do not internalize the social costs of financial institution failure". These higher risks may - in turn - lead to lower bank performance. Similarly, a large strand of literature investigates the impact of gender diversity on the performance of banks as well as of non-banks (e.g. Campbell and Minguez-Vera, 2007; Garcia-Meca et al., 2015; Miller and Triana, 2009; Pathan and Faff, 2013; Ruigrok et al., 2007).

Taken together, occupational diversity appears to be a complex topic in corporate governance research. Various arguments support the view of increased occupational diversity whereas others do not. In order to draw adequate hypotheses one may consider

the sample of this study: the banking business is by far more complex, specific and opaque than most other businesses. The more complex, specific and opaque a certain business is the less occupational heterogeneity may be required to enable a constructive decision making process between board members.

The disadvantages of occupational diversity may increase with regard on returns in the crisis period, as quick reactions are less likely due to time-consuming decision-making processes of a diverse board. This may hinder banks with diverse boards to keep returns up. Moreover, the author assumes that the more diverse a board is the less financial market knowledge exists among the board. This is reasonable by considering the variety of occupational groups on the board of this sample (see Appendix B). Hence, the author expects still a negative relationship with regard on returns in the post-crisis period, since diverse boards may lack of knowledge with regard on the necessity of shifting assets (due to the low interest policy driven from the ECB during that period):

H3: Board diversity negatively affects returns at all times.

Concerning the risk measures, the author expects diverse boards to follow a less risky investment strategy in the pre-crisis period since different perspectives from members with dispersed backgrounds may prevent the bank from dominating roles of risk-takers (financial experts) and their investment-strategies (see Appendix B for a more thorough impression). This may lead to improved risk-ratios for banks with occupational diverse boards during the crisis. At the same time, risk-aversion may (similar to the crisis period) still dominate diverse boards in the post-crisis period due to the lessons learned from the financial crisis. For this reason, the author expects better risk-ratios (less risk) for banks with occupational diverse boards.

H4: Board diversity leads to less risk at all times.

4.2.3 Board Size

Boards from banks differ from non-banks with regard on board size: banks tend to exhibit larger boards (Andrés et al., 2012; García-Meca et al., 2015; Kroszner and Strahan, 2001). However, the banking literature is ambiguous with regard on the impact of board size on performance. Pathan and Faff (2013) investigate a sample of 300 Bank Holding Companies (BHCs) from the US between 1997 and 2011. Their results show a negative relationship between board size and bank performance. Contrary to this study, Adams and Mehran (2012) show a positive impact of board size on performance. They argue that larger boards have more directors with subsidiary directorships and hence these directors might have experience to deal with complex organizations like BHCs. In addition, De Andres and Vallelado (2008) and Garcia-Meca et al. (2015) are in line with the aforementioned study that board size improves bank performance. However, De Andres and Vallelado (2008) also identify a non-linear effect (yielding an inverted U-shaped relation) of board size. Thus, they conclude that, at first glance, including more members into the board improves the monitoring and advisory function. Nevertheless, the positive effect turns negative in the case that the board contains more than 19 members. They state that increasing coordination and decision-making problems as well as free-rider problems outweigh the positive effects.

Minton et al. (2014) do not measure any effects of board size on stock returns during the pre-crisis and crisis period. Results from the study of Erkens et al. (2012) are similar since they do not measure any impact of board size on stock returns during the crisis period. Since time is limited during board meetings, especially large boards may face difficulties to perform the number of important tasks related to bank returns. The fact that there are various channels for banks to generate returns might even worsen this issue. Hence, the author assumes that large boards are less efficient in managing returns, since time-consuming discussions may negatively affect advising processes. Since this issue does not change over time, the author formulates the board size hypothesis as follows:

H5: Board size negatively affects bank returns at all times.

Minton et al. (2014) find a negative relation between board size and bank risk (measured by the volatility of stock returns) in the pre-crisis period (2003 to 2006). They state that large boards require compromises among members, which may lead to less variable stock returns. However, when they use the Tier-1 capital ratio as a measure for bank risk they do not find any significant effect in the pre-crisis period. Since the author assumes that the larger the board the more perspectives contribute to improved monitoring, the author postulates the hypothesis as:

H6: Board size leads to less risk at all times.

4.3 Data and empirical research method

The author uses hand-collected (from www.bundesanzeiger.de) annual balance sheet, income statement and board structure data available from 336 cooperative banks (1806 observations) from Germany between 2006 and 2011 (board structure data is not available from 2005). Since mergers may bias estimation results, the author decided to drop all banks who were part of a merger. This results in a final sample of 246 banks and 1476 observations. The board structure data includes information about the occupational background of each board member. The author developed 27 occupational groups (Appendix B) and related each board member to one occupational group. The advantage of this approach is that the author is able to control for changes in board composition over time. The author further collected the total number of all board members from each bank.

Table 4.1 Sample Selection.

	Observations
Initial sample of cooperative banks from Germany with balance sheet and income statement data from 2006 to 2011 from the German "Bundesanzeiger".	1806
Less: Banks being part of a merger between 2006 and 2011.	-330
Final Sample	1476

This setting is in particular beneficial in terms of running an analysis whose outcomes would clearly identify the channels for the relationship between financial experts on boards and bank performance: Since these banks provide a setup where short-term interests of shareholders play no role, outcomes of the aforementioned link could be solely addressed to the risk-taking nature and skills of financial experts on board. This paper investigates the board structure - bank performance linkage during two periods: the crisis period of 2007 – 2008 and the post crisis period of 2010 – 2011. In order to estimate bank profitability the author refers - as previously mentioned - to common accounting measures like return on equity (ROE), return on assets (ROA) and the net interest margin (NIM). Return on equity (assets) is net income scaled by total equity (assets). Net interest margin is net interest income scaled by all interest generating activities. To assess bank risk, the author uses loan loss provision (LLP) as a proxy for credit and commercial paper risk. Hence, LLP is loan loss provision scaled by all interest generating activities. The figure shows positive values, hence higher depreciations equal higher positive values in loan loss provision. The author further uses EQUITY as a proxy for bank risk. EQUITY is the amount of total equity scaled by total assets. Finally, the author applies a liquidity ratio (LIQ) to assess bank liquidity risk. The author calculates LIQ as all liquid short-term assets scaled by total demand deposits.[37]

As mentioned in section 4.2, the author uses three different measures of board structure: board size (BS), occupational diversity (DIV) and financial experts (FIN). Board size is the number of directors on each board. As the data contains the occupational background of each board member, the author develops a measure of occupational diversity by applying the Herfindahl-Hirschman Index for concentration:

$$\text{DIV} = 1 - \left(\frac{A}{TOTAL}\right)^2 + \ldots + \left(\frac{X}{TOTAL}\right)^2 \qquad (1)$$

[37] See Appendix A for details concerning the definition of variables used.

Where A is the share of occupational group A (e.g. lawyers) from total board members (TOTAL). There are 27 occupational groups in the sample (see Appendix B for detailed information). Consequently, DIV measures the degree of occupational diversity of each bank. The higher the value of DIV the more diverse is the board (e.g. 0 means that all board members pertain to the same occupational group). The author further calculates the financial expert (FIN) variable as the share of all members with a financial background to total board members. Auditors (1%), Tax-advisors (32%) and Managers (67%) such as accountants, financial consultants and other financial management related employees pertain to this group (see Appendix B). This measure indicates whether this group of financial experts is better able to advise and monitor management than other board members due to their specific financial knowledge and occupational proximity to the banking business.

The natural logarithm of total assets (TA) controls for differences in bank asset size. In order to control for differences in capital endowment, the author includes EQUITY. The author drops this control variable in the regressions when the author uses EQUITY as dependent variable (as a measure for bank risk). LOAN is the ratio of loans to total assets to control for differences in the asset side of banks. Banks with a higher ratio of loans to assets hold fewer securities and other commercial papers in their portfolio. If banks with more loans held fewer risky securities and other commercial papers, the author assumes these banks to perform better during the crisis due to the turbulences on the commercial paper market during that period. As a pendant to the characterization of the asset side, the author uses the ratio of deposits to total assets to characterize funding stability. Deposits of cooperative banks are (due to the safeguard mechanism of cooperative banks and deposit insurance from the government) not subject to bank runs. Since funding rates rose heavily in the interbank-lending market, the author expects banks with higher dependence on money market funding to have performed worse during the crisis.

In summary, the author applies the following regression model:

$$Y_{i,t} = \beta_0 + \beta_1 \mathrm{BS}_{i,t} + \beta_2 DIV_{i,t} + \beta_3 FIN_{i,t} + \beta_4 \ \mathrm{Ln}(TA)_{i,t} + \beta_5 \ EQUITY_{i,t} + \beta_6 \ LOAN_{i,t} + \beta_7 \ DEP \ + \varepsilon_{i,t} \quad (2)$$

where i denotes each bank and t the time period (2007 – 2008 or 2010 – 2011). Y_i captures one of the aforementioned performance variables. The coefficients $\beta_1,\ldots,\beta_{11}$ are the independent variables and ε is the disturbance term.

4.4 Descriptive Statistics

Table 4.2 reports descriptive statistics for the bank performance variables, board characteristics and relevant control variables for the full sample of 246 cooperative banks during the period 2006 to 2011. The numbers indicate that board size varies largely over the sample from small boards of two members up to large boards of 29 members. The mean board size of cooperative banks is 6.77, which is smaller than the board size of 12.75 reported from Minton et al. (2014) and 10.77 from Aebi et al. (2012). Around 15.90% among all board members are financial experts, which is also less than 23.33% from Minton et al. (2014) and 22.47% from Aebi et al. (2012). The sample used in this study exhibits much smaller banks (mean total assets of 343.21 Million Euro) compared to the large publicly traded US bank holding companies with median assets of $2.9 billion from Minton et al. (2014) and the US banks with mean asset value of $17.81 billion from Aebi et al. (2012). Notably is also the large variation in bank size ranging from 21 Million € up to 4.6 Billion Euro. Large banks are commonly better diversified than small banks. As a result, large banks may be less vulnerable to economic disruptions and hence may tend to take more risk than small banks. This may affect the board structure - bank performance linkage, especially during the crisis period. In order to tackle this issue this study performs further analyses of subsamples of large and small banks.

Table 4.2 Descriptive statistics of all (246) cooperative banks over the period 2006 to 2011.

	Mean	Median	SD	Min.	Max.
Full Sample					
ROE	0.0524	0.0459	0.0309	-0.1337	0.3032
ROA	0.0032	0.0027	0.0020	-0.0062	0.0124
NIM	0.0244	0.0247	0.0038	0.0068	0.0399
LLP	0.0040	0.0037	0.0028	0	0.0282
EQUITY	0.0603	0.0583	0.0133	0.0261	0.1190
LIQ	0.2478	0.2122	0.1526	0.0177	2.0544
BS	6.7724	6	3.4227	2	29
DIV	0.6825	0.72	0.1415	0	0.8889
FIN	0.1590	0.1429	0.1752	0	0.8333
TA*	343.21	230.25	407.96	21.05	4,607.32
LOANS	0.5443	0.5467	0.1119	0.2146	0.9016
DEP	0.7697	0.7750	0.0660	0.4787	0.9229
ID	0.2686	0.2608	0.0798	0.0012	0.6514

*in Million Euro

The deposit ratio shows that cooperative banks are heavily relying on deposit financing. Finally, the income diversification figure[38] (used in the robustness section) indicates that there are banks who rely heavily on interest income whereas there are also banks who generate more non-interest income than interest income.

Table 4.3 reports the development of relevant board variables over time. Board size is decreasing from 2006 to 2011, possibly indicating that cooperative banks consider the general perception that smaller boards are more efficient. Occupational diversity remains quite constant whereas the ratio of financial experts on boards increases. This development is quite similar to the study from Minton et al. (2014) and hence appears to meet the demand for more financial experts on the board of banks.

Table 4.4 shows the correlation matrix for all dependent and independent variables used in the following regressions. All independent variables show a correlation below 0.4

[38] See Appendix A for the construction of this variable.

except total assets (TA) and board size (BS) who show a correlation of 0.61. The degree of correlation is higher than in other studies: Minton et al. (2014) report a correlation of 0.35 and Aebi et al. (2012) show a correlation of 0.43 between these two variables. However, the author definitely needs to include these variables in order not to face a possible omitted variable bias.

Table 4.3 Development of the board structure of cooperative banks from 2006 to 2011

YEAR	Obs.	BS	DIV	FIN (%)
2006	246	7.25	0.69	14.69
2007	246	7.03	0.69	15.41
2008	246	6.80	0.68	15.62
2009	246	6.62	0.68	16.36
2010	246	6.48	0.68	16.40
2011	246	6.45	0.68	16.90

In addition there is a correlation of -0.76 between the LOAN and the MRISK[39] (MRISK is a measure of market risk and employed as a robustness test in section 4.6) variable. For this reason, the author replaces the LOAN variable with the ID (income diversification) variable in order to run the robustness test.

Finally, the table supports the view concerning the linkage of large banks: they are better diversified which displays a significant positive correlation of 0.11 between the two (TA and ID) relevant variables.

Due to possible collinearity issues the author checked the variance inflation factor (VIF) for all regressions in this study: the highest mean VIF measured equals 1.64 which is well below the critical threshold of 10 and hence further supports model validity.

[39] The definition of the measure of market risk (MRISK) is explained in the robustness section and in Appendix A.

Table 4.5 reports descriptive statistics for the subsamples of large and small banks over the crisis period 2007/08 and the pre-crisis year 2006. Splitting criterion is the median asset size. Interestingly, all (mean) performance variables are better for small banks. Thus, it appears that on average large banks suffered more during the crisis. This in turn may be a result of the possibility that large banks relied more on interbank-lending than small banks. The lower deposit-to-asset ratio supports this notion.[40] In addition, the drying up of liquidity for large banks during the crisis period may reason this issue. The decrease in average liquidity for large banks during the crisis is -23.67% (compared to 2006) whereas the decrease for small banks is just -13.17%. The ROE figure indicates that large banks were on average more profitable before the crisis but less profitable during the crisis than small banks: the average decrease in ROE for large banks during the crisis is around -37.66% compared to the ROE in 2006.

The average decrease in ROE for small banks is about -35.66%. This reveals a heavy negative decrease in bank performance for both subsamples during the crisis. The minimum ROE figure also shows that all small banks remained profitable (positive ROE and ROA) during the crisis. The splitting also reveals the differences in terms of board size across the two subsamples: large banks have a median board size of 8 members whereas small banks have a median board size of 5 members. The largest board for small banks exhibits 13 members compared to 29 members of large banks. In addition, large banks exhibit a higher degree of occupational diversity (mean of 0.72) on their board. Similarly, large banks have on average more finance experts on their board than small banks. This is not surprising as requirements for board members increase by bank size due to increased complexity and opacity (e.g. due to higher diversification, increased capital market exposure etc.). The income diversification figure supports the assumption that large banks are on average better diversified. A possible explanation for the worse (average) performance indicators for large banks could be that large banks overestimated their benefits of diversification. Another explanation may clearly be the higher

[40] In unreported tests I cross-checked the total amount of interbank lending and financing for small and large banks. The exposure for interbank lending and financing for large banks is on average more than 4 times higher than for small banks.

Table 4.4 Correlation matrix of relevant regression variables.

	ROE	ROA	NIM	LLP	EQUITY	LIQ	MRISK	FIN	BS	DIV	TA	LOAN	DEP	ID
ROE	1.00													
ROA	0.92***	1.00												
NIM	0.20***	0.27***	1.00											
LLP	-0.19***	-0.15***	0.12***	1.00										
EQUITY	0.08**	0.41***	0.27***	0.04	1.00									
LIQ	-0.03	0.01	0.01	0.14***	0.10***	1.00								
MRISK	-0.04*	-0.08***	-0.11***	-0.02	-0.15***	-0.14***	1.00							
FIN	0.04	0.01	0.03	-0.05**	-0.02	0.01	-0.06**	1.00						
BS	-0.03	-0.06**	-0.15***	0.06**	-0.14***	-0.23***	0.04	-0.10***	1.00					
DIV	-0.05*	-0.05*	-0.01	0.01	-0.04	-0.11***	-0.02	-0.07***	0.32***	1.00				
TA	0.09***	-0.04	-0.30***	-0.04*	-0.40***	-0.33***	0.03	0.02	0.61***	0.25***	1.00			
LOAN	0.17***	0.19***	0.19***	0.06**	0.10***	-0.02	-0.76***	0.09***	-0.04	0.03	0.03	1.00		
DEP	-0.02	-0.02	0.18***	-0.06**	0.04	0.17***	0.13***	0.04	-0.05**	0.03	-0.15***	-0.31***	1.00	
ID	-0.01	-0.00	-0.35***	0.34***	-0.03	0.09***	-0.14***	-0.01	0.16***	0.11***	0.11***	0.05*	-0.18***	1.00

Table 4.5 Descriptive statistics of large and small cooperative banks over the pre-crisis year 2006 and the crisis period 2007/08.

	Mean	Median	SD	Min.	Max.
Panel A: Large Banks (123 Banks)					
ROE	0.0389	0.0370	0.0240	-0.1337	0.0979
ROE_{2006}	0.0624	0.0550	0.0338	0.0160	0.1549
ROA	0.0022	0.0019	0.0014	-0.0062	0.0074
ROA_{2006}	0.0036	0.0030	0.0023	0.0007	0.0120
NIM	0.0212	0.0215	0.0035	0.0068	0.0288
NIM_{2006}	0.0239	0.0242	0.0033	0.0105	0.0317
LLP	0.0045	0.0043	0.0025	0	0.0142
LLP_{2006}	0.0068	0.0060	0.0037	0	0.0304
EQUITY	0.0552	0.0547	0.0103	0.0263	0.0903
$EQUITY_{2006}$	0.0563	0.0558	0.0095	0.0314	0.0908
LIQ	0.2389	0.2112	0.1223	0.0313	1.1858
LIQ_{2006}	0.3130	0.2821	0.2103	0.0365	2.0544
BS	8.841	8	3.778	3	29
DIV	0.72	0.76	0.1317	0	0.88
FIN	0.1676	0.1429	0.1696	0	0.8333
TA*	540.01	411.90	453.13	218.05	4,0770.02
LOANS	0.5486	0.5535	0.0972	0.2626	0.7729
DEP	0.7538	0.7489	0.0586	0.6073	0.9229
ID	0.3023	0.3052	0.0727	0.0564	0.5472
Panel B: Small Banks (123 Banks)					
ROE	0.0397	0.0361	0.0186	0.0065	0.1295
ROE_{2006}	0.0617	0.0545	0.0293	0.0063	0.1381
ROA	0.0026	0.0023	0.0014	0.0005	0.0094

ROA_{2006}	0.0041	0.0037	0.0023	0.005	0.0119
NIM	0.02352	0.0234	0.0032	0.0099	0.0364
NIM_{2006}	0.0261	0.0261	0.0034	0.0145	0.0388
LLP	0.0043	0.0041	0.0027	0	0.0127
LLP_{2006}	0.0070	0.0067	0.0035	0	0.0224
EQUITY	0.0645	0.0624	0.0138	0.0383	0.1190
$EQUITY_{2006}$	0.0653	0.0628	0.0130	0.0420	0.1157
LIQ	0.3106	0.2837	0.1464	0.0628	0.9693
LIQ_{2006}	0.3577	0.3138	0.2044	0.0661	1.4336
BS	4.9919	5	2.0543	3	13
DIV	0.6504	0.6667	0.1390	0	0.8333
FIN	0.1427	0	0.1754	0	0.6667
TA*	113.26	109.33	58.29	21.32	226.66
LOANS	0.5413	0.5374	0.1241	0.2832	0.9016
DEP	0.7866	0.8046	0.0747	0.5090	0.9055
ID	0.2735	0.2704	0.0688	0.0182	0.4628

dependence on macroeconomic developments from large banks through their greater exposure in interbank lending and larger size itself (total asset exposure). Taken together, board size, other bank characteristics and performance variables differ across bank size substantially and hence may affect the board structure – bank performance linkage. This further supports the purpose to differentiate between large and small banks while running the empirical analysis.

4.5 Empirical results

4.5.1 The financial crisis of 2007/08

Minton et al. (2014) identify that financial experts on the board of banks relate negatively to bank performance during the crisis of 2007 – 2008. Since the authors do not examine the channels for this finding, it remains unclear whether these findings accrue due to financial experts who act in the interest of shareholders or due to the risk-taking attitude of financial experts itself. If this study reveals similar results, these findings could solely arise due to the risk-taking attitude of financial experts since short-term shareholder interest play no role for cooperative banks. In the following, the author runs T-tests and Wilcoxon-tests before performing the regressions in order to obtain a first impression about the differences among banks with and without financial experts on the board.

Table 4.6 reports T-tests and Wilcoxon-tests for banks with and without financial experts on the board. To pertain to column 1 a board needs to exhibit at least one financial expert. This results in 294 observations with at least one financial expert on the board and a control group of 198 observations without a financial expert on the board during the crisis period of 2007 – 2008. The table shows no significant relationship between financial experts on the board and bank returns (ROE, ROA, NIM) during the crisis. In addition, test results suggest that there appears not to exist any relation between financial experts and the level of loan loss provision.

However, the Wilcoxon-test shows - concerning the equity and liquidity figures - some evidence that banks with financial experts on the board appear to hold less equity and less liquidity. This may suggest that financial experts on the board may choose more risky banking strategies. Concerning the board structure variables, financial experts are on larger boards with higher occupational diversification. One reason for this finding might be that the tests also show that banks with financial experts appear to be generally larger in terms of

total assets. This is in line with Table 4.5 since larger banks have on average larger boards, higher occupational diversity and more financial experts on their board.

However, in order to obtain some more substantial evidence with regard on the relationship between financial experts on the board and bank performance during the crisis, this study proceeds by running multivariate analyses. These analyses are crucial since various independent variables correlate (as shown by Table 4.4) with each other and as well with the dependent bank performance variables. The paper proceeds by first running regressions for the full sample of 246 banks and subsequently for the subsamples of large and small banks during the crisis period. This may reveal the necessity to split samples when board structure variables and bank performance differ largely by bank size.

Table 4.6 T-tests and Wilcoxon-tests for banks with and without financial experts on the board during the financial crisis 2007 – 2008.

	FIN=1			FIN=0			Difference (1 – 2)	
	Obs.	Mean (1)	Q_{50}	Obs.	Mean (2)	Q_{50}	t-test P-Value	Wilcoxon P-Value
ROE	294	0.0390	0.0363	198	0.0396	0.0374	0.7856	0.9587
ROA	294	0.0023	0.0020	198	0.0024	0.0022	0.4632	0.4697
NIM	294	0.0224	0.0227	198	0.0223	0.0222	0.9523	0.6009
LLP	294	0.0044	0.0044	198	0.0043	0.0041	0.5930	0.6573
EQUITY	294	0.0591	0.0572	198	0.0609	0.0591	0.1412	0.0984*
LIQ	294	0.2700	0.2281	198	0.2819	0.2665	0.3543	0.0306**
BS	294	7.4558	6	198	6.1161	6	0.0000***	0.0000***
DIV	294	0.7147	0.75	198	0.6414	0.6667	0.0000***	0.0000***
Ln(TA)	294	19.3291	19.4495	198	18.9029	18.9916	0.0000***	0.0000***
LOAN	294	0.5561	0.5579	198	0.5284	0.5332	0.0066***	0.0054***
DEP	294	0.7670	0.7720	198	0.7749	0.7920	0.2138	0.1609

T-tests use the mean and Wilcoxon-tests use the median to calculate statistical significance. (*, **, *** capture 10%, 5% and 1% of statistical significance).

Table 4.7 reports estimates for the full sample regarding the impact of the three board structure variables and various control variables on return on equity (ROE). By running these regressions, the author estimates the standard deviation of the error term by clustering on the bank level. Column 1 reports regression results by including only board size as a board structure variable. Results show some evidence that board size relates negatively to return on equity. Similarly, occupational diversification appears to reduce bank returns during the crisis period (column 2), whereas financial experts (column 3) are not related to bank performance.

However, column 4 shows that board size is no longer significant when estimating all board structure variables within the same regression. Nevertheless, the coefficient of occupational diversity (DIV) remains significant on the 5% level. Thus - as expected - occupational diversity may hamper the decision-making process of the board and hence affect returns negatively during the crisis period. Especially in turbulent periods, disadvantages of heterogeneous boards may become more prevalent due to a higher speed of informational developments. Diverse boards seem to struggle by translating informational processes into effective actions hence reasoning the negative impact on bank returns. Equity appears to affect bank performance positively. One potential explanation might be that returns build up equity and hence banks with high equity have proven to be profitable in earlier periods, which remains constant in the crisis period. Similarly, banks with more loans yield higher returns. This finding is not controversial since the lending business contributes largely to returns for cooperative banks. For brevity, this study reports results in the following only for the full regression model with all board structure variables included in the same regression.[41]

[41] All other regression results are available from the author upon request.

Table 4.7 Regression results of return on equity (ROE) on board structure variables for all 246 cooperative banks.

The table reports results from OLS regressions for the years 2007 and 2008 of the financial crisis.

VARIABLES	(1) ROE	(2) ROE	(3) ROE	(4) ROE
BS	-0.0007* (0.0004)			-0.0006 (0.0004)
DIV		-0.0166*** (0.0056)		-0.0141** (0.0057)
FIN			0.0022 (0.0058)	0.0006 (0.0056)
Ln(TA)	0.0020 (0.0017)	0.0009 (0.0012)	0.0001 (0.0012)	0.0023 (0.0017)
EQUITY	0.2051** (0.0954)	0.1821** (0.0884)	0.1698* (0.0902)	0.2083** (0.0937)
LOAN	0.0407*** (0.0088)	0.0433*** (0.0086)	0.0417*** (0.0089)	0.0419*** (0.0089)
DEP	0.0141 (0.0158)	0.0158 (0.0154)	0.0125 (0.0156)	0.0160 (0.0156)
Constant	-0.0401 (0.0379)	-0.0134 (0.0316)	-0.0054 (0.0320)	-0.0389 (0.0381)
Observations	492	492	492	492
R^2	0.0681	0.0700	0.0597	0.0754
F	7.291	8.791	6.657	6.535

Variable definitions are in Appendix A. Estimations are performed by clustering on the bank level. Robust standard errors are in parentheses (*, **, *** indicate 10%, 5% and 1% of statistical significance).

Table 4.8 Regression results of bank performance variables (ROA, NIM, LLP, EQUITY, LIQ) on board structure variables for all 246 cooperative banks.

The table reports results from OLS regressions for the years 2007 and 2008 of the financial crisis.

VARIABLES	(1) ROA	(2) NIM	(3) LLP	(4) EQUITY	(5) LIQ
BS	-0.0000	0.0001*	0.0001	0.0008***	-0.0044*
	(0.0000)	(0.0001)	(0.0000)	(0.0002)	(0.0025)
DIV	-0.0009**	0.0013	-0.0009	0.0018	-0.0461
	(0.0004)	(0.0016)	(0.0009)	(0.0050)	(0.0520)
FIN	-0.0001	0.0008	-0.0008	0.0024	0.0146
	(0.0004)	(0.0011)	(0.0007)	(0.0051)	(0.0432)
Ln(TA)	0.0001	-0.0016***	-0.0000	-0.0080***	-0.0347**
	(0.0001)	(0.0003)	(0.0002)	(0.0010)	(0.0134)
EQUITY	0.0507***	0.0240	-0.0010		-0.2152
	(0.0061)	(0.0161)	(0.0129)		(0.6444)
LOAN	0.0027***	0.0115***	0.0003	0.0155**	-0.0527
	(0.0005)	(0.0019)	(0.0012)	(0.0071)	(0.0871)
DEP	0.0008	0.0115***	-0.0016	0.0006	0.3328**
	(0.0009)	(0.0029)	(0.0021)	(0.0134)	(0.1397)
Constant	-0.0046**	0.0354***	0.0062	0.1961***	0.7848**
	(0.0022)	(0.0066)	(0.0048)	(0.0256)	(0.3509)
Observations	492	492	492	492	492
R^2	0.2741	0.3529	0.0130	0.2369	0.1654
F	21.31	18.53	0.927	12.35	9.169

Variable definitions are in Appendix A. Estimations are performed by clustering on the bank level. Robust standard errors are in parentheses (*, **, *** indicate 10%, 5% and 1% of statistical significance).

Table 4.8 reports estimates for the full sample of 246 cooperative banks of return on assets (ROA), net interest margin (NIM), loan loss provision (LLP), equity capital (EQUITY) and the liquidity ratio (LIQ) as dependent variables. The author applies in each regression the same regression model, except for column 4: In this regression, the author excluded the equity-to-assets ratio from the regression since this is the dependent variable.

Board size is highly significant in column 4. Thus, large boards appear to improve bank stability by increasing the amount of equity capital. Contrary to expectation, the impact of large boards on the liquidity ratio is negative and significant on the 10% level.

One potential reason may be that time is limited during board meetings and hence large boards may focus on the most important bank stability indicator namely equity. Similar to Table 4.7 occupational diversification negatively relates to return on assets. This confirms the view that heterogeneous bank boards may lack of effective decision making-processes. Finally, the author does not measure any impact from financial experts on the board and bank performance during the crisis period. Thus, the author cannot confirm hypothesis 2 that financial experts lead to greater risk during that period.

LOAN shows no significant relation to loan loss provision, hence indicating that banks with a higher share of loans (to total assets) appear not to yield higher levels of loan loss provision. DEP is positive and significant on a 5% level in column 5, which is reasonable, since short term deposit financing (as a part of total deposit financing) contributes to a higher share of liquid assets (to total assets).

As the descriptive statistics in Table 4.5 already revealed, board structure and bank performance appears to vary largely across large and small banks. Hence, Table 4.9 reports regression results for the subsample of large banks during the 2007 – 2008 crisis period.

Results for large banks remain very similar to the full sample. Board size is now highly significant and negatively related to the liquidity ratio. Moreover, the positive effect on net interest margin is no longer significant for large banks. This may suggest that small banks may cause the effect in Table 4.8. However, there is some evidence on a 10% level that board

size reduces return on assets. This may suggest that boards of large banks solely pay attention towards banks stability in terms of increasing the equity-to-assets ratio. Table 4.5 revealed that large banks comprise larger boards. Since time is limited during board meetings, board members of large banks appear to focus on the most crucial factor of bank stability (EQUITY). This comes at a cost of lower liquidity and may negatively affect returns (ROA) as well. Occupational diversity, however, is now on a 1% level negatively related to ROE and ROA. Similar to the issue of large boards, occupational diversity may be detrimental in turbulent times since heterogeneous groups may face difficulties (due to heterogeneous knowledge) in keeping decision-making processes efficient. This appears to cause decreasing bank returns. The financial expert variable (FIN) remains insignificant for the subsample of large banks.

Table 4.10 reports regression results for the subsample of small banks. The table reveals why it is important to run the regressions from Table 4.8 for the subsamples as well: small banks appear to cause the positive impact (on a 10% level) of board size on net interest margin.

Hence, board size appears to have beneficial effects in terms of return (NIM) and risk (equity) during the crisis solely for small banks. This appears to be a reasonable result since boards from small banks are much smaller. Thus, increasing board size for these banks may add additional knowledge and perspectives to the board and hence strengthen bank performance during crisis periods. Consequently, larger boards of small banks appear to be still small enough (according to Table 4.5 the maximum board size for small banks exhibits 13 members, which is still not very large) to run decisions effectively.

Occupational diversity relates negatively to loan loss provision and the liquidity ratio. Since column 4 exhibits a low F-value, one can conclude that occupational diversity appears to be detrimental for small banks by leading just to less liquidity. Contrary to large banks, occupational diversity does not negatively influence return measures (ROE, ROA) for small banks in crisis periods. Similar to previous regressions the author does not measure any

Table 4.9 Regression results of bank performance variables (ROE, ROA, NIM, LLP, EQUITY, LIQ) on board structure variables for large cooperative banks.

The table reports results from OLS regressions for the years 2007 and 2008 of the financial crisis.

	(1) ROE	(2) ROA	(3) NIM	(4) LLP	(5) EQUITY	(6) LIQ
BS	-0.0008	-0.0000*	0.0001	0.0001	0.0006***	-0.0078***
	(0.0005)	(0.0000)	(0.0001)	(0.0000)	(0.0002)	(0.0026)
DIV	-0.0228***	-0.0013***	0.0021	-0.0002	0.0068	0.0874
	(0.0076)	(0.0004)	(0.0022)	(0.0013)	(0.0055)	(0.0606)
FIN	0.0030	0.0001	0.0014	-0.0005	-0.0040	-0.0731
	(0.0088)	(0.0005)	(0.0019)	(0.0009)	(0.0054)	(0.0583)
Ln(TA)	0.0068*	0.0004*	-0.0018***	-0.0004	-0.0069***	-0.0007
	(0.0040)	(0.0002)	(0.0006)	(0.0005)	(0.0019)	(0.0205)
EQUITY	0.6396***	0.0741***	0.0486*	0.0157		-0.2816
	(0.1978)	(0.0112)	(0.0269)	(0.0222)		(1.2666)
LOAN	0.0214	0.0015	0.0121***	0.0023	0.0266***	0.0791
	(0.0157)	(0.0009)	(0.0032)	(0.0020)	(0.0099)	(0.1609)
DEP	0.0377	0.0014	0.0126**	-0.0008	-0.0018	0.3573*
	(0.0252)	(0.0014)	(0.0049)	(0.0030)	(0.0160)	(0.2038)
Constant	-0.1486*	-0.0105**	0.0366***	0.0108	0.1692***	-0.0263
	(0.0872)	(0.0048)	(0.0137)	(0.0096)	(0.0448)	(0.5276)
Obs.	246	246	246	246	246	246
R^2	0.0992	0.2756	0.2931	0.0324	0.2218	0.0938
F	3.876	10.25	8.838	1.017	9.054	2.759

Variable definitions are in Appendix A. Estimations are performed by clustering on the bank level. Robust standard errors are in parentheses (*, **, *** indicate 10%, 5% and 1% of statistical significance).

Table 4.10 Regression results of bank performance variables (ROE, ROA, NIM, LLP, EQUITY, LIQ) on board structure variables for small banks.

The table reports results from OLS regressions for the years 2007 and 2008 of the financial crisis.

	(1) ROE	(2) ROA	(3) NIM	(4) LLP	(5) EQUITY	(6) LIQ
BS	-0.0009	-0.0001	0.0003**	0.0001	0.0015***	-0.0019
	(0.0006)	(0.0000)	(0.0001)	(0.0001)	(0.0005)	(0.0054)
DIV	-0.0048	-0.0004	-0.0002	-0.0025*	-0.0056	-0.1574**
	(0.0091)	(0.0006)	(0.0014)	(0.0014)	(0.0072)	(0.0757)
FIN	-0.0020	-0.0003	0.0008	-0.0004	0.0088	0.0579
	(0.0074)	(0.0005)	(0.0013)	(0.0010)	(0.0090)	(0.0638)
Ln(TA)	-0.0027	-0.0002	-0.0019***	0.0003	-0.0070***	-0.0711***
	(0.0024)	(0.0002)	(0.0004)	(0.0004)	(0.0025)	(0.0229)
EQUITY	0.0394	0.0419***	0.0090	-0.0139		-0.4303
	(0.0824)	(0.0058)	(0.0185)	(0.0164)		(0.7298)
LOAN	0.0478***	0.0032***	0.0106***	-0.0014	0.0095	-0.1293
	(0.0113)	(0.0007)	(0.0025)	(0.0014)	(0.0098)	(0.0891)
DEP	0.0041	0.0007	0.0105***	-0.0023	-0.0030	0.2698*
	(0.0187)	(0.0012)	(0.0037)	(0.0029)	(0.0199)	(0.1401)
Constant	0.0661	0.0019	0.0420***	0.0036	0.1862***	1.6063***
	(0.0490)	(0.0033)	(0.0088)	(0.0080)	(0.0490)	(0.4963)
Obs.	246	246	246	246	246	246
R^2	0.1352	0.3057	0.2816	0.0404	0.1039	0.1914
F	6.448	17.61	6.965	1.513	3.051	3.875

Variable definitions are in Appendix A. Estimations are performed by clustering on the bank level. Robust standard errors are in parentheses (*, **, *** indicate 10%, 5% and 1% of statistical significance).

significant effect of financial experts on any performance indicator. Thus, financial experts appear neither to have any significant positive nor any significant negative effect for cooperative banks during the crisis period. This result is contrary to the study of Minton et al. (2014) who measure that financial experts relate negatively to bank performance during the recent financial crisis. Thus, it appears that shareholder pressure and not the risk-taking attitude of financial experts causes their results.

Summarizing the crisis period, results indicate that it can prove important to run regression for subsamples with large variation in board structure and performance: increasing board size is beneficial for small banks whereas it is controversial for large banks. Occupational diversification negatively affects returns for large banks and not those of small banks. Finally, financial experts on the board of banks do not appear to affect bank performance significantly.

4.5.2 The post-crisis period of 2010/11

Minton et al. (2014) suggest that financial experts on the board of listed banks increase returns (stock performance) and risk (lower Tier-1 capital ratio) during normal times (from 2003 to 2006). Thus, it appears reasonable to investigate whether financial experts increase returns (ROE, ROA, NIM) for a sample of non-listed banks at a cost of higher risk (higher loan loss provision, lower equity-to-assets ratio and lower liquidity ratio) in the post-crisis period of 2010 – 2011. The period of 2010/11 can be marked as normal times (even if the banking market is still struggling during that period due to low interest rates) as most of the bank performance variables in Figure 4.1 to Figure 4.6 appear to be on a relatively similar level as in the pre-crisis year of 2006. In addition, an unexpected event (as in 2007 – 2008) does not characterize this period.

Table 4.11 reports T-tests and Wilcoxon-tests for the banks with and without financial experts on the board. There are 304 observations with at least one financial expert on the board and a control group of 188 observations without a financial expert on the board during

the post-crisis period of 2010 – 2011. The table shows some evidence (T-test) that banks with financial experts on the board may achieve higher returns (ROE). However, there appears to be also some evidence that banks with financial experts on the board relate to lower net interest margins (Wilcoxon-test). Potential explanations could be, that e.g. the non-interest business, the cost-side exposure or depreciations - which all are not captured by the net interest margin - cause diverging relations.

Table 4.11 T-tests and Wilcoxon-tests for banks with and without financial experts on the board during the post crisis period 2010 – 2011.

	FIN=1			FIN=0			Difference (1 – 2)	
	Obs.	Mean (1)	Q_{50}	Obs.	Mean (2)	Q_{50}	t-test P-Value	Wilcoxon P-Value
ROE	304	0.0602	0.0512	188	0.0548	0.0497	0.0777*	0.3184
ROA	304	0.0036	0.0030	188	0.0034	0.0030	0.1958	0.5153
NIM	304	0.0257	0.0256	188	0.0260	0.0257	0.2804	0.0982*
LLP	304	0.0031	0.0029	188	0.0035	0.0033	0.1239	0.3534
EQUITY	304	0.0604	0.0588	188	0.0619	0.0597	0.2387	0.0984*
LIQ	304	0.1758	0.1550	188	0.1923	0.1687	0.0745*	0.0791*
BS	304	6.7993	6	188	5.9255	5	0.0018***	0.0008***
DIV	304	0.7067	0.7469	188	0.6317	0.6667	0.0000***	0.0000***
Ln(TA)	304	19.4455	19.5037	188	19.0367	18.1004	0.0000***	0.0000***
LOAN	304	0.5473	0.5446	188	0.5240	0.5393	0.0259**	0.0417**
DEP	304	0.7727	0.7721	188	0.7703	0.7755	0.6774	0.9301

T-tests use the mean and Wilcoxon-tests use the median to calculate statistical significance. (*, **, *** capture 10%, 5% and 1% of statistical significance).

In addition, test results suggests that there appears not to exist any relation from financial experts and the level of loan loss provision. However, similar to table 4.6, test results concerning the equity and liquidity figures show some evidence that banks with financial experts on the board appear to hold less equity and less liquidity. This may suggest that financial experts on the board may choose more risky banking strategies at all times. Concerning the board structure variables, results remain similar to the crisis period.

Table 4.12 reports mixed results about the impact of board size on bank performance in normal times. First, board size is highly significant in both the ROE and ROA regression. Thus, it appears that large boards face difficulties in generating returns especially in normal times. This confirms hypothesis 5 partly, since this does not apply to the crisis period. By considering columns 4-6, the picture according to board size seems to become clearer: it appears that large boards appear to foster solely the capital endowment of a bank and neglect all other performance indicators. Since Table 4.7 and 4.8 show no significant effect of board size on ROE and ROA, one potential interpretation might be that large boards met more frequently and appeared to find quicker decisions in crisis periods in order to prevent banks from decreasing returns. In the post-crisis period, large boards may have returned to less frequent meetings, which may result in the negative relationships of board size and returns (ROE and ROA). In turn, the finding of the crisis period – that large boards solely focus on the capital endowment – also applies to the post-crisis period. The fact, that the negative impact on liquidity becomes more significant may support the explanation that board meetings may be less frequent in normal times. In addition, there is some evidence that large boards appear to neglect their monitoring role, as the impact on loan loss provision is now significant on a 10% level. Thus, large boards seem to neglect various parts of their monitoring and advising functions since they achieve an effective group consensus only for the capital endowment of a bank. This comes at a cost of a higher risk exposure (less liquidity and more loan loss provision) and lower returns (ROE and ROA). Regarding occupational diversification and financial experts, results show no evidence related to bank performance.

Table 4.12 Regression results of bank performance variables (ROE, ROA, NIM, LLP, EQUITY, LIQ) on board structure variables for all 246 cooperative banks.

	(1) ROE	(2) ROA	(3) NIM	(4) LLP	(5) EQUITY	(6) LIQ
BS	-0.0023*** (0.0007)	-0.0001*** (0.0000)	0.0001 (0.0001)	0.0001* (0.0001)	0.0008*** (0.0003)	-0.0058*** (0.0021)
DIV	-0.0189 (0.0132)	-0.0009 (0.0007)	0.0011 (0.0017)	0.0001 (0.0008)	0.0036 (0.0057)	-0.0212 (0.0316)
FIN	0.0048 (0.0117)	0.0000 (0.0007)	-0.0004 (0.0011)	-0.0009 (0.0007)	0.0021 (0.0052)	0.0074 (0.0288)
Ln(TA)	0.0134*** (0.0027)	0.0008*** (0.0002)	-0.0007** (0.0003)	-0.0003* (0.0002)	-0.0070*** (0.0010)	-0.0259*** (0.0085)
EQUITY	0.2213 (0.1428)	0.0688*** (0.0109)	0.0479*** (0.0160)	0.0112 (0.0105)		0.6508 (0.5234)
LOAN	0.0528*** (0.0166)	0.0030*** (0.0010)	0.0062*** (0.0022)	-0.0003 (0.0012)	0.0159** (0.0079)	-0.0025 (0.0641)
DEP	0.0522 (0.0354)	0.0026 (0.0019)	0.0151*** (0.0036)	-0.0049** (0.0021)	-0.0047 (0.0143)	0.1164 (0.1027)
Constant	-0.2569*** (0.0662)	-0.0190*** (0.0036)	0.0206*** (0.0064)	0.0126*** (0.0039)	0.1836*** (0.0224)	0.6036*** (0.2099)
Obs.	492	492	492	492	492	492
R^2	0.1304	0.2427	0.1624	0.0407	0.1648	0.1875
F	5.515	10.79	6.208	2.546	9.209	12.29

The table reports results from OLS regressions for the post-crisis period 2010 and 2011. Variable definitions are in Appendix A. Estimations are performed by clustering on the bank level. Robust standard errors are in parentheses (*, **, *** indicate 10%, 5% and 1% of statistical significance).

Similar to the crisis approach this paper proceeds by reporting results for the subsamples of small and large banks in order to further investigate the previous findings. For

large banks, Table 4.13 shows that board size is solely detrimental as it decreases returns and increases risk. Results are significant on a 1% level. Since large boards of large banks made it during the crisis to stabilize equity it appears that they are not able to do so in the post-

Table 4.13 Regression results of bank performance variables (ROE, ROA, NIM, LLP, EQUITY, LIQ) on board structure variables for large cooperative banks.

	(1) ROE	(2) ROA	(3) NIM	(4) LLP	(5) EQUITY	(6) LIQ
BS	-0.0024*** (0.0008)	-0.0001*** (0.0000)	0.0000 (0.0001)	0.0000 (0.0001)	0.0004 (0.0003)	-0.0068*** (0.0024)
DIV	-0.0360* (0.0194)	-0.0022** (0.0010)	0.0022 (0.0024)	-0.0007 (0.0013)	0.0121* (0.0063)	-0.0259 (0.0372)
FIN	0.0218 (0.0197)	0.0009 (0.0010)	0.0010 (0.0020)	-0.0024** (0.0010)	-0.0005 (0.0055)	-0.0292 (0.0335)
Ln(TA)	0.0084 (0.0054)	0.0005* (0.0003)	-0.0017*** (0.0006)	-0.0004 (0.0004)	-0.0069*** (0.0019)	-0.0083 (0.0136)
EQUITY	0.5535** (0.2387)	0.0978*** (0.0158)	0.0373* (0.0225)	0.0151 (0.0170)		-0.0592 (0.5004)
LOAN	0.0403 (0.0326)	0.0020 (0.0016)	0.0065** (0.0029)	0.0022 (0.0018)	0.0204** (0.0096)	0.0319 (0.0874)
DEP	0.0767 (0.0609)	0.0029 (0.0032)	0.0079 (0.0054)	-0.0073* (0.0037)	-0.0135 (0.0189)	0.1435 (0.1324)
Constant	-0.1757 (0.1294)	-0.0134** (0.0065)	0.0450*** (0.0113)	0.0162** (0.0081)	0.1838*** (0.0367)	0.2707 (0.3369)
Obs.	246	246	246	246	246	246
R^2	0.1397	0.3093	0.1622	0.0941	0.1753	0.1159
F	4.134	8.780	3.336	3.053	6.806	3.354

The table reports results from OLS regressions for the post-crisis period 2010 and 2011. Variable definitions are in Appendix A. Estimations are performed by clustering on the bank level. Robust standard errors are in parentheses (*, **, *** indicate 10%, 5% and 1% of statistical significance).

crisis period. Board size seems to be solely detrimental for large banks in normal times. Consequently, results confirm hypothesis 5 (board size relates negatively to bank returns) only for the subsample of large banks. Similar to the crisis period (Table 4.9) occupational diversity hampers returns, which confirms hypothesis 3.

However, there is now some evidence (on a 10 % level) that occupational diversity fosters bank stability (Column 5). Except this positive effect, occupational diversity appears rather detrimental in crisis periods as well as in normal times for large cooperative banks. The financial expert figure (FIN) is now significant on a 5% level in column 4. Thus, financial experts appear better in performing their monitoring and advising role in terms of reducing loan loss provision. Regarding the monitoring function, financial experts may have appropriate skills to detect risks in early stages. Subsequently, they may advise management more quickly how to manage those risks so that they do not become prevalent for the bank. One possible example could be that financial experts detect customers who struggle to repay their loans earlier and advise management to extend the refunding period at lower rates.

According to Table 4.10, board size relates positively to bank performance for small banks during the crisis period. Results for normal times are very similar (Table 4.14): Board size affects loan loss provision positively. However, the F-test shows that the estimation is not meaningful. At the same time, board size remains positively related to equity capital. Thus, board size helps small banks to increase bank stability. Consequently, results confirm hypothesis 6 for the subsample of small banks. With regard on occupational diversification and financial experts on the board, results show no significant effects.

Taken together, results concerning normal times are contrary to the study of Minton et al. (2014). Minton et al. (2014) measure that financial experts are related to less equity-capital at the onset of the crisis indicating that financial experts are prone to more risky banking strategies in normal times. Thus, one may expect the same relation in a sample of cooperative banks for the post-crisis period 2010/11. However, results show no significance concerning this relation. With regard to other risk measures used in this study, the author even identifies

that financial experts reduce loan loss provision for large banks in the post-crisis period. Moreover, results do not show that financial experts strive for higher returns.

Table 4.14 Regression results of bank performance variables (ROE, ROA, NIM, LLP, EQUITY, LIQ) on board structure variables for small cooperative banks.

	(1) ROE	(2) ROA	(3) NIM	(4) LLP	(5) EQUITY	(6) LIQ
BS	-0.0014	-0.0001	0.0002	0.0002**	0.0017***	-0.0058
	(0.0016)	(0.0001)	(0.0002)	(0.0001)	(0.0006)	(0.0039)
DIV	-0.0087	-0.0004	-0.0003	-0.0002	-0.0067	0.0071
	(0.0156)	(0.0010)	(0.0018)	(0.0012)	(0.0084)	(0.0502)
FIN	-0.0099	-0.0006	-0.0012	0.0002	0.0066	0.0123
	(0.0123)	(0.0009)	(0.0015)	(0.0011)	(0.0090)	(0.0515)
Ln(TA)	0.0095**	0.0007**	-0.0006	-0.0005	-0.0065**	-0.0439**
	(0.0045)	(0.0003)	(0.0006)	(0.0003)	(0.0026)	(0.0171)
EQUITY	0.0695	0.0547***	0.0465**	0.0044		1.0633
	(0.1714)	(0.0137)	(0.0194)	(0.0139)		(0.7573)
LOAN	0.0505***	0.0031**	0.0060**	-0.0016	0.0139	-0.0202
	(0.0181)	(0.0013)	(0.0030)	(0.0016)	(0.0113)	(0.0824)
DEP	0.0431	0.0030	0.0198***	-0.0041	-0.0028	0.0574
	(0.0403)	(0.0023)	(0.0048)	(0.0026)	(0.0205)	(0.1263)
Constant	-0.1752*	-0.0169***	0.0150	0.0154**	0.1757***	0.9463***
	(0.0981)	(0.0063)	(0.0108)	(0.0066)	(0.0497)	(0.3557)
Obs.	246	246	246	246	246	246
R^2	0.0761	0.2130	0.1975	0.0452	0.0856	0.1158
F	1.724	4.316	4.157	1.279	2.819	3.561

The table reports results from OLS regressions for the post-crisis period 2010 and 2011. Variable definitions are in Appendix A. Estimations are performed by clustering on the bank level. Robust standard errors are in parentheses (*, **, *** indicate 10%, 5% and 1% of statistical significance).

In summary, the results provided in this paper show that financial experts on the board of cooperative banks do neither perform worse than other board members during the financial crisis nor do they increase returns at a cost of higher risk in normal times (post-crisis period). Contrary, results show evidence that they seem to use their financial knowledge in order to contribute to bank stability (measured by loan loss provision) in a long-term perspective. This may suggest that financial experts on the board of banks where short-term shareholder interests play no role use their financial knowledge and understanding of risks to provide stability to the bank rather than running for returns at a cost of (unforeseeable) high risks.

4.6 Endogeneity and robustness tests

Endogeneity is vital concern as in any other corporate governance study. In order to reduce reverse causality concerns, the author ran robustness tests with lagged independent variables. Results are very similar. Furthermore, the independent variables used in this study could correlate with other bank characteristics the author cannot control for, which may cause endogeneity issues as well. Since there is no valid instrument to apply in order to mitigate those concerns, one may interpret results in a cautious way. Another possible issue may be an omitted variable bias, especially concerning past performance variables as indicators for present bank performance. However, the inclusion of a lagged dependent variable into the regression may cause autocorrelation problems and bias results as well. Nevertheless, in order to mitigate those concerns the author additionally ran all regressions again by including the lagged dependent variable into the regressions. Results remained robust. Furthermore, outliers could cause biased results. Hence, the author performed another robustness test by cutting data for all regressions on a 3 percent level. Again, results remained robust.

Since the equity ratio is the most important accounting indicator for bank stability, the author tested another definition of equity capital, namely extended equity. This figure equals total equity, plus fund for general banking risks, plus special items related to currency

conversion, plus participation rights, plus subordinated liabilities all scaled by total assets. Results remained robust to the EQUITY (as dependent variable) regressions performed in this study.

The author further ran sensitivity tests for different definitions of small and large banks. Results remain qualitatively similar up to the threshold definition for small banks < 40^{th} percentile and large banks > 60^{th} percentile (in terms of total assets). This may limit the explanatory power of the results for the subsamples provided in this study.

Biased results may also arise due to neglecting appreciations in the definition of loan loss provision. There are 20 observations during the period 2007/08 and 50 observations during the period 2010/11, which report appreciations instead of depreciations. Neglecting these appreciations and using 0 as a "cutoff-threshold" for depreciations may cause biased results. This may be in particular important in order to verify whether the positive influence (negative relationship) of financial experts on loan loss provision for large banks during the post-crisis period remains robust. In order to tackle this issue, the author ran further robustness tests by including appreciations into the loan loss provision variable. Once again, results remained robust.

Different results compared to those from Minton et al. (2014) may also arise due to differences in the definition of financial experts. The authors definition of financial experts is somewhat broader than their definition. Since occupational backgrounds vary between these samples, outcomes may not fully be transferable. However, in order to further verify results concerning the definition of financial experts, the author also excluded tax advisors (since this group may be in particular less risk-taking) from the definition of financial experts and ran the regressions again. By doing so results remained unchanged.

Results may also differ from Minton et al. (2014) due to the diversity variable (DIV) employed in this study. Since this variable has not been investigated in bank governance research so far, the author drops this variable and adds the more common ratio of independent

directors, which Minton et al. (2014) use in their study as well, and runs all regressions once more.[42] Again, results remain qualitatively similar.[43]

Another potential reason could be that the risk measures the author applies do not cover all possible risk exposures of a bank. Consequently, the author performs an additional robustness test in the following: The author employs another risk indicator, namely market risk[44] (MRISK) to assess whether the employed board structure variables (and in particular financial experts) affect market risk exposure.

Figure 4.7 shows that there is a high increase in market risk exposure from 2008 to 2009. The (mean) market risk exposure increased from 24% (of total assets) in 2008 up to over 29% in 2009. This may be a reaction to the low interest policy performed by the ECB. Since MRISK captures different risks than the previous bank risk variables used, the variable may be in particular suitable to further verify the link between board structure and bank risk. Since LOAN is highly correlated (0.74) with MRSIK the author drops LOAN and include ID[45] (income diversification) in the following regressions. Table 4.15 reveals whether board structure variables employed in this study relate to the exposure of market risk. Interestingly, the table shows no significant correlation except the impact of financial experts in the post-crisis period (column 5): financial experts on the boards of large cooperative banks appear to reduce market risk exposure during the 2010/11 period.

[42] The author thanks Prof. Renée Adams (Business School of Banking and Finance, University of New South Wales) for suggesting this additional robustness test.
[43] Results for all additional robustness tests are available from the author upon request.
[44] Market risk is 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).
[45] See Appendix A for the definition of income diversification (ID).

Figure 4.7 Development of the (mean) market risk exposure (MRISK) over the period 2006 to 2011.

The relation is highly significant on a 1% level. The author interprets this outcome as further evidence that financial experts on the board of large cooperative banks reduce bank risk in normal times, which is again contrary to the results from Minton et al. (2014). The economic impact concerning this finding is also reasonable: Adding an additional financial expert to the board decreases market risk exposure by 24.62 %. Considering the mean market risk exposure of 28.94 % this is a significant change in market risk exposure.

This confirms the view that financial experts are rather contributing than deteriorating bank stability when short-term shareholder interests play no role. Thus, results show no evidence that the risk-taking attitude of financial experts leads to decreasing bank performance. This applies to the crisis period as well as to the post-crisis period. In contrast, results suggest that financial experts on the board of a sample of non-listed (cooperative) banks follow rather long-term objectives since they reduce bank risk even in the aftermath

Table 4.15 Regression results of bank performance variables (MRISK) on board structure variables for the full sample and subsamples of large and small cooperative banks.

The table reports results from OLS regressions for the crisis period 2007/08 (Column 1 – 3) as well as for the post-crisis period 2010/11 (Column 4 – 6).

	(1) MRISK Full	(2) MRISK Large	(3) MRISK Small	(4) MRISK Full	(5) MRISK Large	(6) MRISK Small
BS	0.0028 (0.0025)	0.0028 (0.0029)	0.0013 (0.0042)	0.0044 (0.0035)	0.0038 (0.0038)	0.0047 (0.0057)
DIV	-0.0189 (0.0473)	-0.0612 (0.0652)	0.0083 (0.0613)	-0.0313 (0.0551)	-0.0826 (0.0776)	-0.0306 (0.0703)
FIN	-0.0424 (0.0385)	-0.0798 (0.0543)	-0.0115 (0.0551)	-0.0518 (0.0419)	-0.1494*** (0.0473)	0.0482 (0.0654)
Ln(TA)	-0.0053 (0.0105)	-0.0065 (0.0193)	-0.0015 (0.0192)	-0.0158 (0.0118)	-0.0107 (0.0198)	0.0025 (0.0225)
EQUITY	-1.5958*** (0.6014)	-1.3504 (0.8516)	-1.7171** (0.7981)	-1.6038** (0.6950)	-0.9958 (0.7943)	-1.9565** (0.9292)
DEP	0.2303** (0.0909)	0.0453 (0.1495)	0.3549*** (0.1152)	0.2431* (0.1266)	-0.0269 (0.1838)	0.3748** (0.1602)
ID	0.0057 (0.0927)	0.0265 (0.1441)	-0.0143 (0.1126)	-0.0949 (0.1303)	0.0091 (0.1781)	-0.1838 (0.1838)
Constant	0.2552 (0.2295)	0.4363 (0.4030)	0.0855 (0.3944)	0.5292** (0.2498)	0.6335 (0.4045)	0.1147 (0.4234)
Obs.	492	246	246	492	246	246
R^2	0.0690	0.0527	0.1106	0.0684	0.1067	0.1115
F	2.158	1.153	2.287	1.850	2.194	2.020

"Full" shows regression results for the full sample of 246 cooperative banks. "Large" shows regression results for the 123 largest banks, whereas "Small" shows results for the 123 smallest banks. Splitting criterion is the median of total assets. Column 1 – 3 show regression results for the crisis period of 2007 – 2008. Column 4 – 6 show regression results for the post-crisis period of 2010 – 2011. All estimations exhibit cluster on the bank level. Robust standard errors are in parentheses (*, **, *** indicate 10%, 5% and 1% of statistical significance).

(post-crisis period) of the financial crisis. This means, that regulators should carefully consider these differences in outcomes that arise due to different ownership structures when imposing new regulatory constraints concerning financial experts on the board of banks.

4.7 Conclusion

This paper asks whether results from the study of Minton et al. (2014) concerning the relationship of financial experts on bank performance apply to cooperative banks. Investigating cooperative banks is crucial in particular for regulators: the results of this study show that financial experts on the board of cooperative banks are neither negatively related to bank performance during the crisis nor during the post-crisis period of 2010 – 2011. For this reason, regulators should consider ownership structure and hence business model of banks when imposing new regulatory constraints for financial experts on the bank board. Results show that contrary to Minton et al. (2014) financial experts on the board of non-listed banks do not relate to worse performance during the crisis. Moreover, they do also not cause higher returns at a cost of higher risk during normal times. Contrary, results indicate that financial experts on the board of large cooperative banks reduce the risk exposure (LLP and MRISK) of those banks during normal times.

This study also shows why it is important to run regressions for subsamples of banks: since board size appears to have positive as well as negative effects for large banks during the crisis it appears to have solely positive effects (higher EQUITY and NIM) for small banks during that period. The author addresses these diverging results to differences in board size between these two subsamples: Large banks tend to have larger boards hence increasing board size for these banks may lead to negative decision-making effects. Contrary, small banks tend to have smaller boards hence increasing board size appears to be beneficial for those banks. Additional board members may provide additional knowledge and further perspectives to the board, which appears to remain still small enough to keep effective

decision-making processes. However, board size seems to become solely detrimental for large banks in normal times. At the same time board size remains beneficial for small banks at all times. This may indicate that especially large banks should decrease board size in order to strengthen their monitoring and advising effectiveness.

Similarly, occupational diversity on the board decreases returns for large banks and decreases liquidity for small banks during the crisis. The negative impact for returns of large banks remains constant in the post-crisis period whereas the negative effect of liquidity for small banks is no longer significant. Thus, it appears that occupational diversity of bank boards is detrimental for large banks at any time. Since the boards of large banks incorporate on average a higher occupational diversity, this may indicate that there are limits of beneficial effects concerning board diversity.

Appendix

Appendix A

Variables	Symbol	Description
Return on Equity	ROE	Net income scaled by total equity.
Return on Assets	ROA	Net income scaled by total assets.
Net interest margin	NIM	Net interest income scaled by all interest generating assets. Subtracting interest expenses from interest income results in net interest income.
Loan Loss Provision	LLP	Loan loss provision over the total gross value of total bank loans. The ratio is reported in positive values hence higher numbers represent higher depreciations.
Equity	EQUITY	Total equity scaled by total assets.
Liquidity	LIQ	Calculated as: (cash assets reserves + overnight debt due + trading assets + inventory on hands + money held in trust)/(total demand deposits)
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)
Board Size	BS	Number of directors on each board.
Occupational Diversity	DIV	Herfindahl-Hirschman Index as a ratio of each occupational group to total board size
Financial Experts	FIN	The share of members with a financial background to total board size. The group of members with a financial background consists of Tax Advisors, Auditors, and other academic employees with a management background
Total Assets	Ln(TA)	Natural logarithm of total assets.
Lending Business Focus	LOANS	Calculated as the share of total bank loans to total assets.
Funding strategy	DEP	Calculated as the share of total customer deposits to total assets

Income diversification	ID	Calculated as: (commission margin + trade margin + other earning assets)/(gross interest margin + commission margin + trade margin + other earning assets)

Appendix B

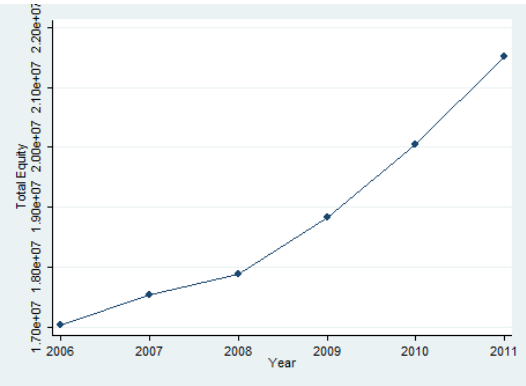
Descriptive statistics of occupational backgrounds from board members based on individual observations from 2006 to 2011.

Occupational background	Mean	SD	Max.
Tax Advisor (FIN)	0.297	0.557	4
Auditor (FIN)	0.009	0.093	1
Manager (FIN)	0.724	1.074	8
Employee	0.310	0.808	7
Employee (Government Service)	0.652	0.848	5
Entrepreneur	0.881	1.241	7
Lawyer	0.164	0.418	3
Doctor	0.081	0.308	2
Politician	0.381	0.670	3
IT	0.012	0.110	1
Engineer	0.304	0.564	4
Pensioner	0.208	0.518	5
Craftsman	0.825	1.180	7
Self-employed Craftsman	0.254	0.599	4
Agriculturalist	1.414	1.558	11
Pharmacist	0.0427	0.202	1
Architect	0.045	0.207	1
Vehicle Driver	0.025	0.156	1
Housewife	0.022	0.148	1
Driving-School Instructor	0.003	0.058	1
Notary	0.001	0.037	1
Chief Judge	0.005	0.069	1
Officer of Justice	0.007	0.082	1
Veterinarian	0.005	0.073	1
Landlord	0.010	0.135	2

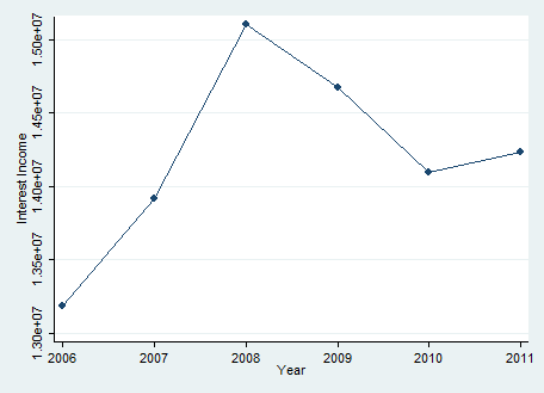
Professor	0.021	0.143	1
Other	0.068	0.948	15

Appendix C

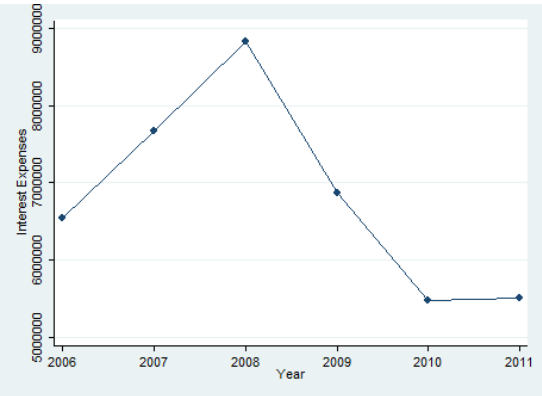
Development of average total equity (absolute values) from 2006 to 2011:



Development of average interest income (absolute values) from 2006 to 2011:



Development of average interest expenses (absolute values) from 2006 to 2011:



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