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The Effect of Industrial Diversification on Banks' Performance

A case study of the Norwegian banking market

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Abstract

By attracting deposits from savers and offering financing to borrowers, banks play an important role in the economy. Which strategic approach banks ought to pursue for optimizing performance and hence contribute to financial stability is a fundamental question in this context. In this thesis, we attempt to answer one aspect of this question by estimating the effect of industrial diversification on bank performance using annual data from 112 banks in Norway over the period 2004-2013. Employing several measures of portfolio diversification, we first estimate the average effect of diversification on bank performance. Then, we investigate whether the effect of diversification on performance is dependent on the underlying bank risk. Our findings suggest that increased diversification improves performance for banks in Norway. Moreover, we find that the effect of diversification is in fact dependent on bank risk. Increased diversification seems to be the superior strategy in low and high risk scenarios, while a more concentrated portfolio should be preferred at moderate risk levels. However, similar studies done in other developed countries find evidence that differs from our results. We address these contrasting results by arguing that differences in country-specific factors such as market structure and risk should be considered in order to make meaningful comparisons.

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1. Introduction

1.1 Motivation and purpose

An efficient financial system is fundamental for promoting growth and prosperity in a society. As intermediaries in financial transactions, banks play a crucial role for this purpose by channelling funds from savers to borrowers with productive investment opportunities. The question of whether banks should diversify or specialize their lending activities is important to consider in this context. Evidence from the financial crisis in 2008-2009 showed that banks' excessive exposure to the US housing market helped trigger what was to become a global crisis. The question concerning diversification versus specialization is therefore not only important to consider for the banks themselves, but also for legislators and regulators in order to ensure financial stability.

Conventional wisdom within traditional banking theory argues that diversification tends to reduce risk and improve banks' performance by emphasizing the reduction in risk as the total credit exposure gets spread across borrowers in different industries. Diamond (1984) and Marinč (2009) explains this decrease in risk as a result of improved monitoring incentives for diversified banks as agency problems between bank owners and bank creditors are being mitigated. However, literature from corporate finance theory claims that banks should concentrate their lending activities to industries where they possess expertize. Mishkin, Matthews, and Giuliodori (2013) suggest that by focusing on a few industries, banks can utilize industry-specific knowledge to better screen out bad credit risks and hence reduce costs arising from asymmetric information. To further examine these issues, Winton (1999) presents a theoretical framework where he points out that the effect of diversification on bank performance may in fact be dependent on the underlying risk level. His model provides several testable hypotheses which have been investigated in the empirical literature. Acharya, Hasan, and Saunders (2006) find support for Winton's (1999) theory when examining the effect of industrial diversification on the return for Italian banks. A similar study was conducted in Germany by Hayden, Porath, and von Westernhagen (2006) and yielded coinciding results. Moreover, findings in these studies indicate that banks on average may benefit from increased portfolio concentration.

In this master thesis, we investigate the relationship between industrial diversification of banks' credit portfolio and performance using a panel of 112 banks operating in Norway over the period 2004-2013. Based on a comprehensive dataset composed of individual bank loans, we first examine the average effect of industrial diversification on banks’ performance. We then go on to test Winton’s (1999) model to assess whether the assertion of risk dependency holds in the Norwegian banking market. Thus, we aim to contribute to the existing literature on this topic by following the footsteps of Acharya et al. (2006), Hayden et al. (2006), and others. To the best of our knowledge, this is the first large-scale research done to investigate this relationship in Norway and we believe it will be of great interest for both market participants and regulatory bodies, as well as for anyone with a general interest in banking and finance.

1.2 Research question

To investigate the relationship between diversification and bank performance, we propose the following research question:

How does diversification in commercial lending affect banks’ performance?

We attempt to answer this question by regressing several measures of diversification on banks’ return on assets.

1.3 Outline

The rest of this master thesis is organized as follows: In **Section 2** we present a brief overview of the banking market in Norway and how it is structured. **Section 3** introduces relevant theory and related empirical research done on this topic. This section discusses different theoretical views on the relationship between diversification and performance as well as previous findings in related empirical research. **Section 4** presents our econometric models, which will later be estimated by using different measures of diversification. **Section 5** gives a description of the treatment of our dataset and the construction of relevant variables we use in our analysis. In **Section 6** we present the descriptive statistics which allows us to comment on trends in the Norwegian banking market over our sample period. The justification for the choice of estimation method is presented in **Section 7,** while our results are provided in **Section 8.** In **Section 9** we discuss the basis for comparing our results to the results of other similar studies. Finally, we present our concluding remarks in section **Section 10**.

2. Background

2.1 Overview

In Norway, banks are either categorized as commercial or saving banks. In 2016, the Norwegian banking market consisted of 136 banks of which 22 were registered as commercial banks while 10 were branches of foreign owned banks (Norges Bank, 2016a). The number of saving banks has been reduced dramatically following the liberalization of the Norwegian banking industry in the 1980's and a subsequent wave of mergers and acquisitions. Before 2002, saving banks were restricted to be organized as self-governing foundations and could only raise external capital by issuing primary capital certificates, later known as equity certificates. Moreover, saving banks have historically focused their operations on personal banking in their respective local communities, whereas commercial banks have been more targeted towards the business segment. After the removal of mentioned restrictions, saving banks could reorganize as limited companies which made the distinction between commercial and saving banks less clear. Furthermore, the Norwegian banking industry is relatively small compared to other developed countries. Norwegian banks' total assets as a share of GDP were about 200% in 2013 (Norges Bank, 2013). In the same year total banking assets to GDP were on average 270% in Euro area countries (European Central Bank, 2015).

2.2 Market characteristics

The decrease in number of banks over the last three decades has been driven by consolidation which in turn has led to increased market concentration. Also, when regulations prohibiting foreign banks to operate in Norway were removed in 1985, large foreign commercial banks entered the market and quickly gained substantial market shares. Today, the three largest foreign-owned banks operating in Norway (Nordea, Handelsbanken, and Danske Bank) have a combined market share in total lending of roughly 20% and close to 30% in the business segment (Norges Bank, 2016b). Another contributing factor to increased concentration has been the mergers and acquisitions conducted by the partly state-owned bank DNB. Since the merger between Norway's two largest banks, Bergen Bank and Den Norske Creditbank in 1990, DNB established itself as Norway's largest financial institution, controlling about one-third of both the private and commercial loan market. Thus, approximately 50% of the total loan market is dominated by the four largest commercial banks. The remaining market is highly fragmented as 125 of the smallest banks have a combined market share of about 28% (Finans Norge, 2015).

2.3 Aggregate loan portfolio and credit risk

Loans to households and businesses constitute the largest part of banks' total assets (approximately 65% on average in our sample period). In particular, banks operating in Norway are highly exposed to the household- and mortgage market, which amounts to about 50% of total loans in 2016 (Norges Bank, 2016b). For Norwegian-owned banks, the share was 62% in 2013 (Norges Bank, 2013). This significant exposure has developed into a growing concern for regulatory authorities in the assessment of financial stability. The low interest rate environment during the last decade in combination with a steadily increase in real wages has contributed to a rapid growth in housing prices, especially in Norway's largest cities. As a result, Norwegian households' debt has increased to historically high levels (Finanstilsynet, 2015). Thus, banks and the wider economy are vulnerable to sudden hikes in interest rates or any shocks that have an adverse impact on employment and households' ability to repay their mortgages.

Loans made to firms operating in commercial real estate, construction, and services constitute over 60% of the credit portfolio in the business segment, where commercial real estate alone amounts to approximately 40% (Norges Bank, 2016b). The Norwegian banking sector is thus relatively concentrated in respect to lending on the aggregated level due to a large exposure to households and commercial real estate, despite significant variations in the composition of each bank's loan portfolio. Moreover, commercial real estate and the construction industry have historically been associated with higher risk and a greater share of losses compared to other industries. Evidence from the Norwegian banking crisis in the period 1988-93 revealed that 38% of total non-performing loans were related to these industries (Kragh-Sørensen & Solheim, 2014).

Notwithstanding a high exposure to households, banks' loan losses are mainly driven by losses incurred in the business segment. Due to the very uncertain nature of doing business and initiating new projects, commercial lending is usually associated with higher credit risk. Nevertheless, loan losses in both segments have been relatively low in Norway since the end of the banking crisis in the 90's. Much of this can be attributed to a period of robust economic growth, substantial increase in real incomes for households, and stable conditions for businesses.

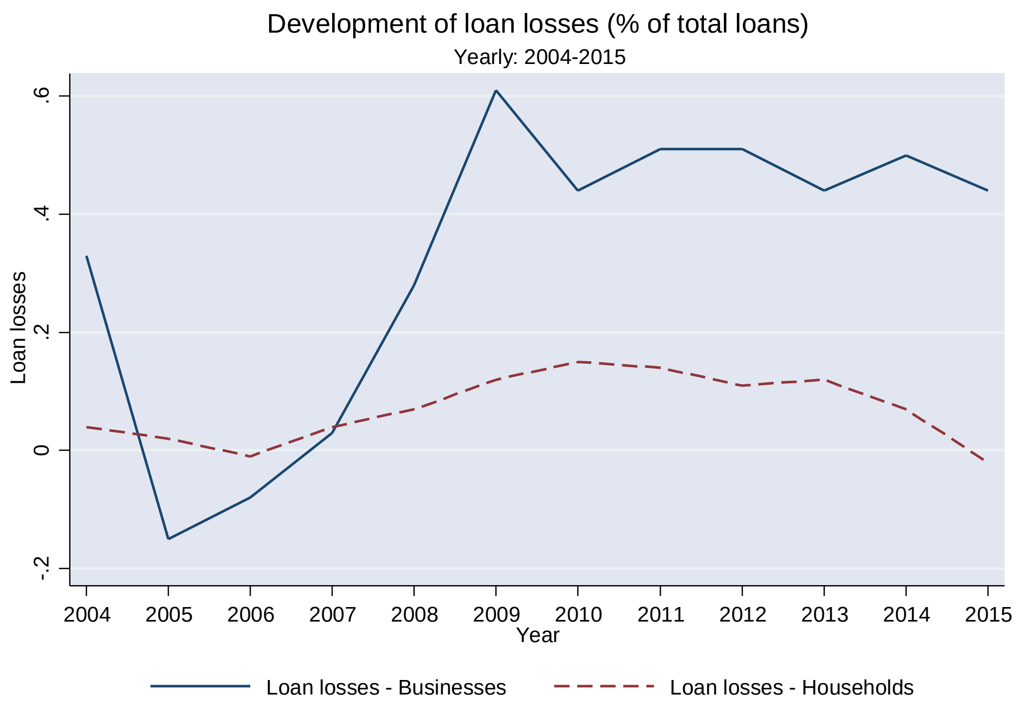

Figure 1

Note: The data is retrieved from Norges Bank.

Figure 1 displays loan losses occurred in the two segments. Based on this data and given a close to equal share of outstanding loans distributed among businesses and households, we can draw the conclusion that losses in commercial lending is the main source of reported loan losses in the banking industry.

3. Related literature

3.1 Theoretical literature

Whether banks and other financial intermediaries should diversify or specialize their loan portfolio is a fundamental question in banking. Theoretical frameworks and models have been developed arguing for both strategies, and there is still no consensus among scholars and professionals. On the one hand, traditional portfolio and banking theory advocates that banks should pursue a diversification strategy and invest across different sectors to reduce the probability of financial distress. On the other hand, theory from corporate finance suggests that firms should adopt a more narrow strategy and focus on activities where they possess expertize.

3.1.1 Traditional banking theory

Conventional wisdom in the literature of financial intermediation and banking argues that spreading lending activities across several geographical regions and industries allow banks to diversify their risk. By investing across a variety of industries and regions with different risk profiles, the bank is less affected by shocks in individual industries. Since banks typically are highly leveraged, the importance of diversification is assumed to be even greater. Moreover, banks’ role as monitors is an essential element in the literature for explaining the benefits of diversification.

Diamond (1984) develops a theory for financial intermediation where he shows how diversification of loan portfolios can reduce the cost of monitoring. Banks serve as agents for its lenders (depositors) and are delegated the task of monitoring loans on behalf of them. His model shows that as the number of depositors and loans made to entrepreneurs with independent projects grows without bound, the contracting costs approaches zero. As a result, banks have an incentive to spread their lending to as many entrepreneurs with uncorrelated projects as possible.

Marinč (2009) follows Diamond’s (1984) view in emphasizing banks’ role as monitors of their lenders and develops a framework to show how diversification can improve monitoring incentives. In the presence of a non-diversifiable systemic shock banks experience a reduction in profits while monitoring costs remain unchanged. Thus, monitoring costs are relatively high in times of turmoil. Consequently, this increases the incentive to stop monitoring and engage in risk-shifting behaviour by transferring all risk to depositors. He argues that a diversified bank will have a lower probability of incurring large losses but a higher likelihood of incurring small losses. This will put bank capital at stake instead of deposits and therefore make monitoring more valuable for shareholders.

Ramakrishnan and Thakor (1984) explain how financial intermediaries act as information producers on behalf of investors and how diversification can improve the process of acquiring information about potential borrowers. In their view, investors endogenously work together and form an intermediary to gather information more efficiently than each investor can achieve on its own. They especially emphasize how diversification among the newly established coalition of information producers reduces agency problems between individual investors and the information producer. It is shown that as the number of uncorrelated firm projects increases, the total agency cost of the intermediary becomes lower than the sum of total agency expenses incurred for each investor.

3.1.2 Corporate finance theory

Theories in corporate finance suggest that a firm should concentrate its activities to utilize its competence and expertize. Denis, Sarin, and Denis (1997) pointed out that companies should specialize to reduce the value-destructive effects of diversification strategies caused by agency problems. To mitigate agency problems a bank has to screen out bad credit risks. Mishkin et al. (2013) argue that a specialized bank can achieve a competitive advantage in collecting information as it becomes more knowledgeable about specific customers and industries. Thus, the bank can perform a more efficient screening and monitoring process which ultimately reduces overall risk.

Literature within corporate finance also point out that different stakeholders may have contrasting views on whether a firm should diversify. According to Martin and Sayrak (2003), risk-averse managers whose compensation relies on company performance are assumed to have an incentive to expand firm activities to reduce firm-specific risks that affect their future compensation. The incentive to diversify also applies to creditors as they are not entitled to the potential upside of risky business projects. From a lender’s point of view, excessive risk-taking by companies reduces the probability of repayment. Shareholders, however, can diversify their own portfolio and may thus prefer firms that pursue a focused strategy in order to increase portfolio returns.

The presence of a “diversification-discount” is also a common argument used by advocates opposed to the idea of firm diversification. Servaes (1996) showed that during the wave of mergers and acquisitions in the 1960’s and 70’s, the firm value of a conglomerate was less than the total value of the company’s individual businesses. Several studies confirmed this result (see Berger & Ofek, 1995, Lang & Stultz, 1994). However, it is important to note that most of the existing literature on specialization versus diversification in corporate finance is written in the context of non-financial firms.

3.1.3 Consistency with portfolio theory

As stated in modern portfolio literature, there is an assumed positive trade-off between risk and return. The concept of the efficient frontier was developed by Harry Markowitz in 1952 and refers to a portfolio with the best possible expected return given its level of risk (Bodie, Kane, & Marcus, 2014). Investors can then, depending on their risk aversion, choose to move along the efficient frontier in an upward-sloping manner that indicates a positive risk-return trade-off. This implies that if in the context of our research topic all banks operate at the efficient frontier, changes in portfolio diversification will have no effect on banks’ performance. In this situation, due to the positive relationship between risk and return, all potential effects of diversification (concentration) will be captured by risk.

3.1.4 Winton’s theory of a non-linear diversification effect

In an attempt to model a bank's choice between different diversification strategies, Winton (1999) develops a framework where he shows that the effect of a diversified loan portfolio on performance strongly depends on the level of sector risk and monitoring incentives. A specialized bank with a loan portfolio exposed to low levels of risk will have a low probability of failure. Diversification will thus have few benefits. Moreover, in the presence of high levels of risk, diversification may increase the likelihood of bank failure; a diversified bank is exposed to more potential sector downturns, which increases the probability of failure. According to his model, benefits of diversification are in fact greatest when the loan portfolio is exposed to moderate risk levels. He justifies this by referring to a risk level high enough to pose a threat of failure if a bank specializes, but not so high that a downturn in one sector is severe enough to cause the failure of a diversified bank. This dynamic implies a non-linear relationship between return and diversification conditioned on the degree of risk. Winton (1999) further argues that whenever increased diversification lessens banks' ability or incentive to monitor, the chance of bank failure increases. For instance, when entering a new sector a bank has to gain thorough understanding and knowledge of the market to develop effective monitoring. Such sectoral knowledge takes time to acquire, and the bank will have a competitive disadvantage against incumbent banks. This is in line with the view of Mishkin et al. (2013) regarding how a specialized bank may benefit from a more efficient screening- and monitoring process due to superior industry knowledge.

It is not clear from a theoretical point of view whether banks should pursue a focused or diversified strategy for their loan portfolios. Different theories present well-founded arguments in support of their respective views. To further investigate the relationship between specialization versus diversification and bank performance, we turn to empirical evidence.

3.2 Empirical literature

Most existing empirical literature on diversification versus specialization in relation to banks' performance and risk have focused on the effect of geographical- and product diversification. Since our objective is to study the effect of industrial diversification of loan portfolios and its impact on banks' return, we choose to focus on studies with a similar approach. Due to lack of data on individual bank loan exposures, only a few studies have investigated this relationship. However, some interesting studies have been conducted.

The preeminent study of this relationship was performed by Acharya et al. (2006). The study uses data from 105 Italian banks in the period 1993-1998 and analyzes the effect of banks' industrial and sectoral loan diversification on both performance (measured by ROA) and risk (measured by doubtful and non-performing loans). To gauge the level of concentration of banks' loan portfolio, they use the Hirschman-Herfindahl Index (HHI). Their results indicate that diversification has a negligible effect on return when downside risk is low but has a slightly positive effect as the risk approaches moderate levels. However, as opposed to the views held within traditional banking theory, diversification deteriorates banks' return when downside risk is high. The authors rationalize this by the risk-shifting effect, where any benefits from monitoring in a high risk scenario accrue only to banks' creditors. Thus, bank owners have limited incentives to monitor. Consequently, diversification is only proven to contribute positively to returns when loans are exposed to moderate risk. Also, the study finds a significant negative relationship between industrial and sectoral specialization and non-performing loans, which may be attributable to a positive effect of industry-specific knowledge and monitoring proficiency. To test the hypothesis that monitoring effectiveness impairs when a bank expands into a new sector or industry, the authors include a variable that measures how recently a bank entered into a new market. The following results reveal that non-performing loans increase when a bank enters a new sector or industry. These findings are consistent with Winton's (1999) views and are explained by less efficient monitoring due to the lack of prior lending experience in the newly entered market.

On behalf of Deutsche Bundesbank, Hayden et al. (2006) examine how industrial, sectorial, and geographical diversification (measured by HHI) affect the return (measured by ROA) of 983 German banks in the period 1996-2002. They use value at risk (VaR) as a proxy for risk rather than non-performing loans. VaR describes the maximum loss that one can expect during a day of normal market movements and is a statistical technique often used to estimate a bank's loan portfolio risk. Their overall findings show that there are no benefits from diversification, regardless of geographical, sectoral, or industrial diversification. However, there is some evidence indicating that banks' profitability tends to increase in the case of more industrial diversification at moderate levels of risk. Thus, their results coincide with Winton's (1999) model and the findings of Acharya et al. (2006); that the effect of diversification is strongly dependent on the underlying risk level and only beneficial in moderate risk scenarios.

Chen, Wei, and Zhang (2013) performed a study where they investigated the effect of sectoral concentration on the risk of 16 Chinese banks in the period 2007-2011 using non-performing loans as a risk measure. An interesting feature of the study is that sectors are risk-weighted by their respective beta-values to capture changes in systematic risk when constructing the concentration measure (HHI). As opposed to Acharya et al. (2006), Chen et al. (2013) find a significant positive relationship between loan portfolio concentration and bank risk, which coincides with the benefits of diversification asserted in traditional banking theory.

Berger, Hasan, Korhonen, and Zhou (2010) did a similar study in the Russian banking market. Their data consist of 1449 banks in the time span 1999-2006. They use a composite index including non-performing loans, the standard deviation of quarterly earnings, and loan loss provisions as proxies for risk, whereas return on assets is applied as a performance measure. Following comparable studies, they employ the HHI to measure the degree of concentration of loan portfolios. They find a non-monotonic relationship between the level of diversification and bank returns. Moreover, a bank with a concentrated loan portfolio is found to be more profitable and less risky up to a certain threshold. In contrast to the Italian banking industry and the ideas of Winton (1999), evidence from the Russian banking market suggests that the advantage from diversification tends to be somewhat stronger at higher risk levels.

A comparable study was performed by Tabak, Fazio, and Cajueiro (2010) where they analyzed the risk-return trade-off in respect of diversification of 96 Brazilian commercial banks over the time span 2003-2009. Their findings indicate that a higher degree of loan portfolio concentration leads, on average, to an increase in return and at the same time a reduction in default risk. Thus, the results show that specialization in lending improves overall financial performance for Brazilian banks.

Evidence from the empirical literature seems to coincide with the views of corporate finance theory regarding diversification. None of the studies above, except Chen et al. (2013), find a strong positive relationship between diversification and bank performance. There is a clear tendency that specialized banks outperform banks with a more diversified loan portfolio. Moreover, the effect of different diversification strategies seems to be dependent on the underlying risk level. This is partly explained by shifts in monitoring incentives as the risk level changes. Whether a similar dynamic exists in the Norwegian banking market is an interesting topic for further investigation.

4. Econometric models

The main purpose of our study is to investigate whether a bank's choice of diversification strategy in commercial lending affects its profitability. Relevant theory and findings from previous research suggest that the choice of diversification strategy is an important determinant for bank performance. To address this, we first consider the average effect of diversification on performance by estimating the following general linear model:

(1) $$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{5} \beta_n X_{nbt} + \gamma_b + \delta z_t + \varepsilon_{bt}$$

In line with other comparable studies, we use return on assets, expressed by ROA_{bt}, as the dependent variable to examine the diversification-performance relationship of banks in Norway. We attempt to estimate our model using different measures of portfolio concentration which have been commonly used in related studies. These concentration measures are represented by CM_{bt}. Loan losses and Z-score are used as proxies for risk, and is expressed by $Risk_{bt}$. X_{nbt} represents a set of control variables and include banks' total assets, personnel costs, and – with the purpose of comparing with other studies – banks' share of equity. γ_b represents bank-specific time-invariant effects, while z_t is a set of year dummies. Finally, the model error term is given by ε_{bt}.

If all banks operate at the efficient frontier, diversification adjustments of their credit portfolio will have no effect on performance due to the positive relationship between risk and return. However, we have no reason to believe that all banks in our sample operate at the efficient frontier and we therefore expect β_1 to be different from zero. This implies that changes in diversification can improve performance by bringing the portfolio closer to the efficient frontier (Hayden et al., 2006). Although previous comparable studies have found evidence in support of specialization and the views advocated in corporate finance theory, our null hypothesis follows the views held by traditional banking theory. It states that a bank should diversify its portfolio to optimize performance. Hence, the concentration coefficients are expected to hold the following sign:

$\beta_1 < 0$

The theoretical framework developed by Winton (1999) emphasizes how the effect of diversification strongly depends on the level of risk. This dynamic represents a non-linear and U-shaped relationship between return and credit portfolio concentration as a function of risk.

In mathematical terms, it can be presented as the first derivative of performance with respect to concentration (diversification) $\frac{\partial ROA}{\partial CM}$, where the benefits of concentration (diversification) reach its minimum (maximum) at moderate risk levels (Acharya et al., 2006). To investigate Winton's (1999) hypothesis of a U-shaped relationship, we expand our general model to the one used by Acharya et al. (2006):

(2) $$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{5} \beta_n X_{nbt} + \beta_6 CM_{bt} * Risk_{bt} + \beta_7 CM_{bt} * Risk_{bt}^2 + \gamma_b + \delta z_t + \varepsilon_{bt}$$

Our null hypothesis in support of a U-shaped relationship between portfolio concentration and return as a function of risk gives the following signs on the coefficients of interest:

$\beta_1 > 0,\ \beta_6 < 0,\ \beta_7 > 0$

The interaction terms $\beta_6 CM_{bt} * Risk_{bt}$ and $\beta_7 CM_{bt} * Risk_{bt}^2$ are included to capture the potential effect of concentration on return for various levels of risk. In other words, the unique effect of concentration on return is no longer limited to $\beta_1 CM_{bt}$, but it also depends on the interaction terms. $\beta_1 CM_{bt}$ will now be interpreted as the partial effect of changes in concentration on return at low risk levels. The resulting implications of a true hypothesis means that a bank should increase the concentration of its credit portfolio in both low and high risk scenarios.

5. Data

5.1 Data sources and treatment of data

The data we use in this thesis originates from different sources. Annual data used to construct the industrial composition of banks' credit portfolio is provided by the Norwegian tax authorities (Skatteetaten). This unique dataset contains detailed information on about 10 million individual loans made to commercial customers by banks operating in Norway in the period 2004-2013. To better identify each registered customer in this dataset, we obtain additional customer information from a database put together by the Institute for Research in Economics and Business Administration (SNF). This dataset contains, among other things, industry codes which represent the particular industry a firm operates in. These industry codes are based on the classification standard developed by Statistics Norway (SSB). Finally, to assess banks' financial performance, we rely on data assembled by Finans Norge and Bankenes Sikringsfond. The dataset contains financial statements for every bank operating in Norway on a non-consolidated level.

Banks in the data assembled by Finans Norge and Bankenes Sikringsfond are not listed with an organization number. Thus, we had to retrieve the organization numbers for each bank from the data provided by Skatteetaten. We choose to omit banks with less than seven years of financial data to ensure that each bank adds significant explanatory power to our analysis. Also, there have been numerous merger activities during the sample period. In cases where two independent banks form a new bank, we omit the two separate banks before the merger and include the newly created bank if it has more than six years of reported data. In the treatment of takeovers, we omit the target bank. These actions are taken to avoid any bias from double counting. We gathered information on mergers and acquisitions from the Norwegian Saving Bank Association (Sparebankforeningen). The association assembles and publishes yearly data on every M&A transaction between saving banks. We merge our final banks and their respective organization numbers with the data collected from Skatteetaten to link each loan to the banks we use in our analysis. The merged data also incorporate loans from banks which are not included in our sample and is thus omitted. Finally, we exclude observations where the loan amount either are registered as zero or are missing. The sorted data consist of just over 1.3 million individual loans divided between 112 banks.

To connect each bank's loan to its customers and their respective industry codes, we merge the sorted data with the database put together by SNF. In years where information on the industrial category of firms is missing, we replace the missing values with the classification used in either the year before or after. Moreover, we omit about 20% of the observations as these loans are made to firms not registered with an industry code. As a consequence, we are left with just over 1 million loan observations. A potential drawback with the omission is that it may affect our diversification measures since a bank's distribution of omitted loans may differ from its distribution of loans in the final dataset. However, examination of the merged dataset after the exclusion reveals that the total distribution of loans among banks and customers is still close to identical as before the omission. Based on this data we can categorize every bank's total loan exposure into different industries for each year in the period 2004-2013. This division forms the basis for calculating various yearly concentration measures of banks' commercial credit portfolio. Finally, after the computation of different concentration measures, we merge this data with our sample banks' financial figures retrieved from Finans Norge and Bankenes Sikringsfond.

Our final sample consists of 112 banks, in which saving banks constitute a vast majority of 97 banks[1]. Thus, our sample captures the underlying characteristics of the Norwegian banking market and the dominant position of saving banks. The sample comprises about 80% of total commercial lending in Norway in the period 2004-2013. The number of banks each year varies between 106 and 112 which gives us 1094 observations in total. Lastly, it is important to note that all mentioned datasets include information on Norwegian banks as well as subsidiaries and branches of foreign-owned banks. Information on loans, however, apply exclusively to Norwegian registered businesses.

5.2 Construction of variables

Given the data available, we decide to employ many of the same variables as used in related studies. This will enhance the comparability of our research and make the results more interesting in an international context.

[1] An overview of our sample banks can be found in appendix 1.

5.2.1 Concentration variables

We will use several measures of portfolio diversification in order to examine whether the results of the analysis are affected differently depending on the choice of measure. Consistent results across different measures will be interpreted as a sign of robustness. The data from Skatteetaten enable us to decompose the loan portfolio of each bank into separate industries. Using the classifications set by SSB, the disaggregated industry breakdown is as follows:

(1) Agriculture, (2) Oil, Gas and Mining, (3) Manufacturing, (4) Energy, (5) Construction, (6) Retail, (7) Shipping, (8) Transportation and Tourism, (9) Telecom, IT and Media, (10) Finance and Insurance, (11) Real Estate, (12) Other Services, (13) Research and Development, (14) Public Sector and Culture.

Hirschman-Herfindahl Index (HHI)

Following comparable studies, our primary measure of diversification is the Hirschman-Herfindahl Index (HHI). It is commonly used to assess the degree of concentration within an industry and often serves as an indicator of market competition. The index is defined as the sum of squares of each firm's market share within an industry and ranges between 1 and 1/n, where HHI of 1 represents a situation of monopoly whereby one company dominates the entire industry. For our purpose as a measure of portfolio diversification, we calculate the HHI as the sum of squares of loan exposures under a given industry classification as a fraction of total loan exposure. Relative exposure of bank b at time t to each industry i is defined as:

$$x_{bti} = \frac{Nominal\ Exposure_{bti}}{Total\ Exposure_{bt}}$$

Hence, the HHI of bank b at time t can be written as:

$$HHI_{bt} = \sum_{i=1}^{n} x_{bti}^2$$

An HHI of 1 represents a specialized bank where all loans are handed out to a single industry, while an HHI of $\frac{1}{n}$ describes a fully diversified bank in which the loan portfolio is equally distributed between industries.

Average Relative Differences (D1)

D1 compares the deviation of a bank's credit portfolio from a benchmark portfolio to the relative size of the industry. Thus, D1 is a distance measure that quantifies the divergence between a bank's portfolio and a benchmark portfolio. In our case, the benchmark portfolio is the banking industry's aggregated credit portfolio. The first to apply this measure was Pfingsten and Rudolph (2002) who argue that D1 has the advantage of taking into account the variation in size of the industries, in addition to being easily calculated. This measure is normalized and gives values between 0 and 1 in which 1 represents maximum concentration.

$$D_1(x,y)_{bt} = \frac{1}{n}\sum_{i=1}^{n}\frac{|x_{bti} - y_{ti}|}{x_{bti} + y_{ti}}$$

Where y_{ti} represents industry's i share of the total benchmark loan portfolio at time t while x_{bti} serve as the fraction of a bank's loan exposure to industry i at time t relative to its total loan exposure.

Shannon Entropy (SE)

Shannon Entropy (SE) is used to measure diversity within systems and is often employed in the ecology literature. Nevertheless, SE can also be applied to gauge the degree of diversification in portfolios (Yu, Lee, & Chiou, 2014). The formula can be expressed as follows:

$$SE_{bt} = -\sum_{i=1}^{n} x_{bti} \cdot ln\left(\frac{1}{x_{bti}}\right)$$

The SE takes on values between 0 and $-ln(n)$, where 0 reflects a bank that is extremely concentrated while $-ln(n)$ illustrates a bank that has a perfect diversified loan portfolio.

5.2.2 Balance-sheet variables

All balance sheet variables are calculated based on yearly bank-specific data provided by Finans Norge and Bankenes sikringsfond. The construction and use of potential variables are thus constrained by the information available in this dataset.

Return on assets (ROA)

Return on assets (ROA) is defined as the ratio of net income to total assets. It is a commonly used performance measure and illustrates how well a firm's management utilizes the resources available to produce profits.

$$ROA_{bt} = \frac{Net\ Income_{bt}}{Total\ Assets_{bt}}$$

When employed to assess the performance of financial firms and banks in particular, ROA needs to be seen in light of their distinctive operations. As a consequence of their business strategy, banks are typically highly levered. Thus, banks and financial firms are likely to achieve a lower ROA compared to non-financial companies, despite earning large profits.

Losses on loans and guarantees as a share of gross lending

A loss is recognized in the income statement as an impairment of loans and guarantees.

$$Loan\ loss_{bt} = \frac{Loan\ Losses_{bt}}{Gross\ Lending_{bt}}$$

When objective evidence of impairment exists, impairment losses on loans are calculated as the difference between the carrying amount and the net present value of estimated future cash flows discounted by the original effective interest rate (DNB, 2013). More technically, loan losses are either classified as specified loan loss provisions or as losses on loans and guarantees. Specified loan loss provisions are estimated losses tied to identified customers and reduce the value of an investment in the balance sheet. Changes in specified loan provisions during the current period is recognized in the income statement as a loss/impairment on loans and guarantees. Most existing studies have employed measures such as non-performing loans, loan loss provisions, the standard deviation of quarterly earnings, and value at risk (VaR) as proxies for risk. However, even though loan losses are not a standard risk proxy in related empirical research, we employ this variable due to lack of information on other commonly used risk measures.

Z-score

Z-score is often used to assess a financial institution's overall risk of insolvency (Li, Tripe, & Malone, 2017). In contrast to other widespread risk measures such as equity betas, credit ratings, and volatility of stock prices, Z-score is an accounting-based risk measure. Due to being merely dependent on accounting data, the Z-score is an attractive risk measure for non-listed financial institutions. We choose to include Z-score as an additional risk proxy since the majority of banks in our sample are non-listed.

$$Z - score_{bt} = \frac{EQ - ratio_{bt} + ROA_{bt}}{\bar{\sigma}_{ROA,bt}}$$

The rationale behind the Z-score is to relate the variability of a bank's return to its capital base. Hence, one gets a clear indication of how much variability in returns that can be absorbed by the capital without the bank becoming insolvent. ROA is often the preferred return measure in this context, whereas the standard deviation of ROA over the period is used as a measure of variability. A bank with a high Z-score is perceived as a low-risk bank since a large number of standard deviations of the bank's ROA need to drop in order to wipe out the capital base. We use a time-varying Z-score to encounter the fact that a bank's risk profile and capital structure changes over time. As stated in the formula above, we calculate the mean standard deviation of ROA over the sample period and use the current equity-to-capital ratio of each year.

Control variables

To obtain more consistent results, we include control variables to ensure that the variables of interest do not capture other external effects that are likely to be related to our dependent variable. By doing this, our estimated parameters will better reflect their true value. Thus, we are more likely to avoid problems caused by omitted variable bias. To account for other plausible factors that may affect a bank's performance, we choose to include the following variables:

$$Size_{bt} = \ln(Total\ Assets)_{bt}$$

The size variable controls for potential effects of scale return. Larger banks can expand operations both in terms of number of customers and geographical presence. A larger customer base may imply more capital available for further investments and growth. However, larger organizations can just as likely suffer from diseconomies of scale, which often will be manifested in bureaucracy and inefficiencies.

$$Personnel_{bt} = \frac{Personnel\ Costs_{bt}}{Total\ Assets_{bt}}$$

We choose to include the ratio of personnel costs to total assets as a proxy for bank efficiency. Personnel costs have historically constituted a significant part of a bank’s operating costs. However, recent developments in technology and especially digitalization have contributed to a general decrease in personnel costs relative to total assets over our ten-year sample period. Thus, banks with a higher ratio of personnel costs are assumed to be relatively less efficient.

$$EQ - ratio_{bt} = \frac{Equity_{bt}}{Total\ Assets_{bt}}$$

The overall risk of a bank and the risk preferences of a bank`s management are likely to be reflected in the amount of equity relative to total assets the bank holds. The inclusion of equity ratio can thus give rise to biased results as the amount of equity might be determined by our risk and concentration variables. To avoid this potential bias we proceed without controlling for the share of equity. However, since some of the other related studies have chosen to include a measure of equity we will nevertheless present additional results where we control for the equity ratio.

6. Descriptive statistics

Table 1 provides summary statistics of the variables we use in our analysis, whereas the correlation matrix is presented in Table 2.

Table 1: Summary statistics for relevant variables in our regression analysis

	Mean	Observations	Median	St.dev	Min	Max
ROA	0.0069	1094	0.0074	0.0070	-0.1058	0.0648
HHI	0.2892	1094	0.2493	0.1502	0.1072	1.0000
D1	0.5323	1094	0.5310	0.1383	0.0771	0.9822
SE	-1.6344	1094	-1.7067	0.3790	-2.3444	0.0000
Loan loss	0.0022	1094	0.0014	0.0041	-0.0109	0.0627
Z-score	43.588	1094	38.653	29.342	1.6547	188.61
Personnel	0.0128	1094	0.0122	0.0062	0.0022	0.1129
Size	8.1422	1094	7.7611	1.4669	5.2832	14.417
EQ-ratio	0.0971	1094	0.0916	0.0410	0.0372	0.7487

Table 2: Correlation matrix

	ROA	*HHI*	*D1*	*SE*	*Loan loss*	*Z-score*	*Personnel*	*Size*	*EQ-ratio*
ROA	1								
HHI	-0.185	1							
D1	-0.121	0.609	1						
SE	-0.179	0.974	0.698	1					
Loan loss	-0.276	0.187	0.104	0.164	1				
Z-score	0.113	-0.105	0.013	-0.082	-0.157	1			
Personnel	-0.432	0.322	0.392	0.319	0.169	-0.053	1		
Size	0.044	0.039	-0.506	-0.053	-0.023	-0.129	-0.384	1	
EQ-ratio	-0.261	0.093	0.279	0.124	0.008	0.137	0.607	-0.429	1

We find several extreme values contained in our dataset. A closer study reveals that most of these observations are consequences of new entries and bank-specific events, especially related to smaller banks. An example of the former is Bank Norwegian, which was established in 2007 and entered the market the same year. The bank underwent two consecutive years with losses wherein the sample minimum return of -10.58% occurred in 2007. Another example related to the latter is Vang Sparebank which suffered a substantial loss in 2011 as a result of a series of unsuccessful projects. An additional explanation for why we observe a higher frequency of extreme values among smaller banks may be that smaller banks, in general, are more sensitive to market fluctuations than their larger competitors. Moreover, we find that banks with the highest and lowest values of return and loan loss in one year are not necessarily the same banks that experience this in other sample years. In fact, we see that approximately 50% of the banks experience one or more years with observations above the upper adjacent value or below the lower adjacent value in terms of both return and loans loss[2]. This means that if one were to omit the extreme values of either loan loss or return, the excluded data points would be associated with 50% of our banks across all years. Furthermore, we would not have been able to consider the overall impact of banks' credit portfolio adjustments on performance during the financial crisis, as many of the extreme values come as a result of this period. Because it is in our interest to capture the effect of concentration also in the case of high risk levels and during times of financial turmoil, an exclusion of the extreme values would not have been reasonable. Thus, we follow Berger et al. (2013) and other mentioned studies, and thereby choose not to omit the extreme values since our motive is to examine the diversification-performance relationship for all banks over the entire sample period.

6.1 Return on assets (ROA)

A bank's sources of revenue can essentially be divided into three main categories; interest income from lending activities, fees and commissions, and gains from financial assets. The relative contribution of each category to a bank's total revenue depends on its asset composition and business model. However, the most important source of revenue for the majority of saving- and commercial banks is interest income from lending. Consequently, the net interest margin, defined as interest income – interest expenses, is an important determinant for a bank's net profit. From the summary statistics, we see that ROA varies from negative 10.58% to positive 6.49%, with a mean (median) value of 0.69% (0.74%). The relatively low mean (median) value are in line with our expectations and comes as a result of their distinctive

[2] Upper adjacent level: $y_{75} + 1{,}5(y_{75} - y_{25})$.
Lower adjacent level: $y_{25} - 1{,}5(y_{75} - y_{25})$.
Where y_{75} and y_{25} represents the 75^{th} percentile and 25^{th} percentile, respectively.

business model, as previously discussed. We also observe an anticipated negative correlation between banks' return and booked losses and personnel costs.

Figure 2 presents the historical development in average ROA for the full sample. The years before the culmination of the financial crisis in September 2008 can be characterized as a period of strong economic growth and credit expansion. Despite lower interest margins due to tougher competition, stricter capital requirements, and lower credit risk, banks experienced increased profits during this period. This can to a great extent be attributed to a high demand for credit and a correspondingly strong growth in lending (Norges Bank, 2007).

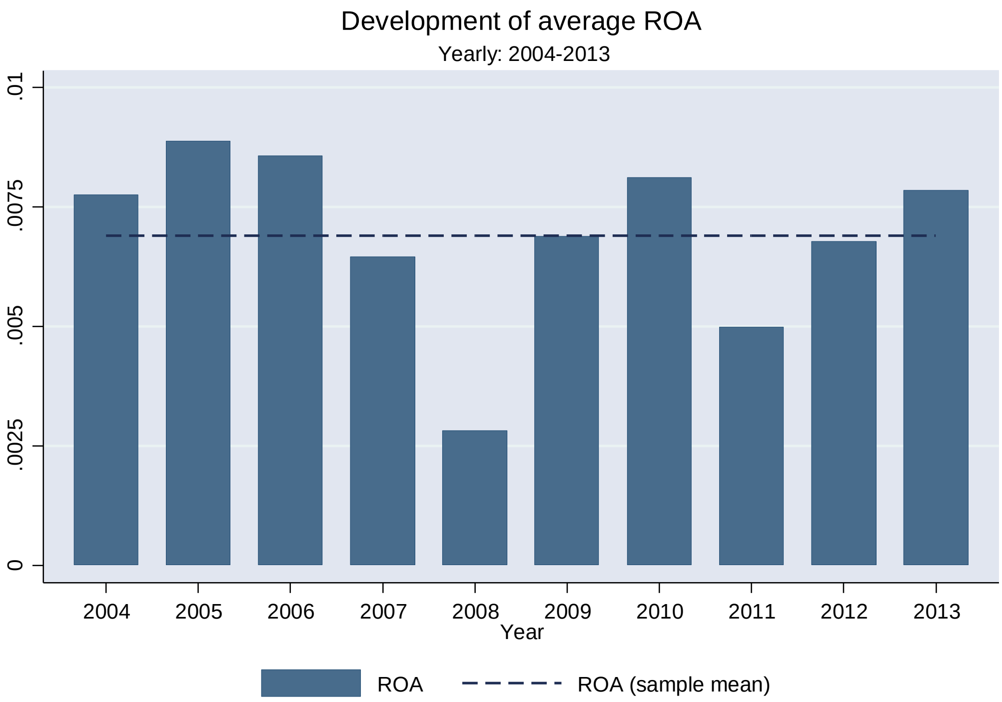

Figure 2

Note: Full sample ROA 2004-2013

The figure also depicts substantial variation in banks' ROA over the sample period and illustrates clearly the negative impact of the financial turmoil in 2008-2009, as well as the relatively rapid recovery. During an economic downturn, more borrowers will typically have difficulties to fulfil their debt obligations. This leads to a higher share of impairments followed by increased costs as these impairments are recognized in banks' income statement. Increased costs due to impairments will often be accompanied by lower demand for credit, which ultimately puts pressure on bank profits. Although banks in Norway and the Norwegian economy in general suffered from the crisis, the period of recession was over in 2009. Actions initiated by the Norwegian government and Norges Bank quickly dampened the spread of uncertainty and reinforced market confidence. The primary element of these actions was to inject liquidity into a dried-up banking system through a swap deal that allowed a set of banks to exchange covered mortgage bonds for highly secure and liquid government bills (Norges Bank, 2009a). A new period of disturbance arose in international financial markets as the European debt crisis peaked in 2009 and took hold the following years. This may have been a contributing factor for the setback in banks' performance in 2011. However, banks' return normalizes as we move towards the end of the sample period and surpasses the sample average in 2013.

6.2 Risk

The mean (median) loss rate is 0.22% (0.14%), although with considerable variation. A few observations are registered with negative loss rates. This occurs when a bank reverses previously recognized losses as new information about the creditworthiness of a customer indicates a reasonable probability of repayment. Even though we see a tendency of large losses being related to smaller banks, institutions such as DNB and Nordea did incur losses large enough to be represented in the top 80th percentile in the year following the financial crisis.

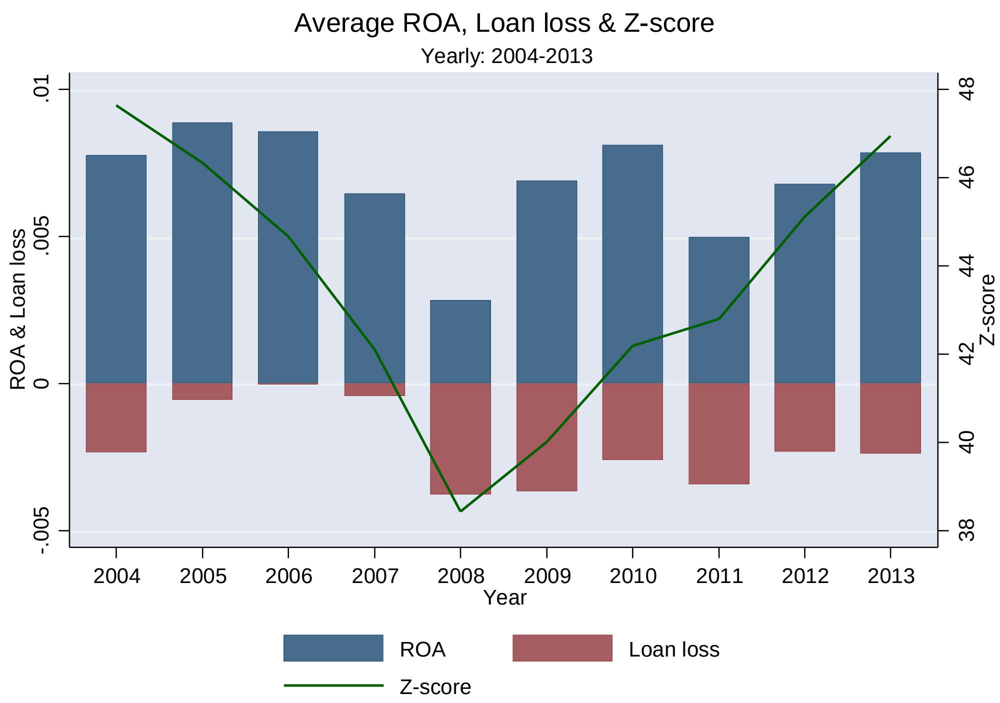

Figure 3

Note: Full sample ROA, loan loss, & Z-score 2004-2013

Due to the soundness of the economy and the low credit risk at the time, the years preceding the financial crisis was a period of high and stable bank returns and correspondingly low loss rates. The loss rate increased considerably in 2008 and has later remained at a higher level despite the economic recovery (see Figure 3 above). Again, as during the banking crisis in the 90's, a large part of losses did occur in the commercial real estate industry (Norges Bank, 2011). The decline in economic activity causes a pessimistic outlook on future economic conditions, which in turn results in lower demand and market prices for renting office buildings and property for commercial use. The high share of losses stemming from real estate is a natural consequence of the large exposure to this particular industry in addition to its sensitivity to economic fluctuations.

Figure 3 reveals that the Z-score had already started to decline considerably before the crisis. This effect was likely to be driven by the simultaneous decline in average ROA, which is part of the numerator in the Z-score computation. Conversely, the decrease in returns in 2011 was not followed by a similar decrease in Z-score, which indicates that the reduction in profits was offset by a strengthening of banks' capital base during this period. Norwegian banks were already relatively well capitalized due to distinctive capital requirements implemented after the previous banking crisis in the 90's. Thus, the financial crisis did not lead to a solidity crisis and a widespread of bankruptcies but was rather seen as a crisis caused by liquidity shortcomings. Nevertheless, governmental actions were undertaken in 2009 in order to increase the core capital of Norwegian banks through the means of capital injections from Statens finansfond (Norges Bank, 2009b). The Z-score increased steadily from 2008, reflecting the improvement in returns as well as a positive development of banks' capital base.

We believe that the relatively low average loss rate during our sample period can be attributed to the general robustness of the Norwegian economy and its banking industry. Moreover, the low level of losses presumably reflects a well-functioning and efficient monitoring system developed by the banks.

6.3 Credit portfolio diversification

The average value of the diversification (concentration) measures indicates that the majority of banks in our sample prefer to diversify their loan portfolios. Moreover, as the correlation matrix illustrates, the diversification (concentration) measures are highly correlated which might indicate that changes in HHI, D1, and SE will have a somewhat similar effect on return. The graph below shows the development of average diversification for the total of banks in our sample.

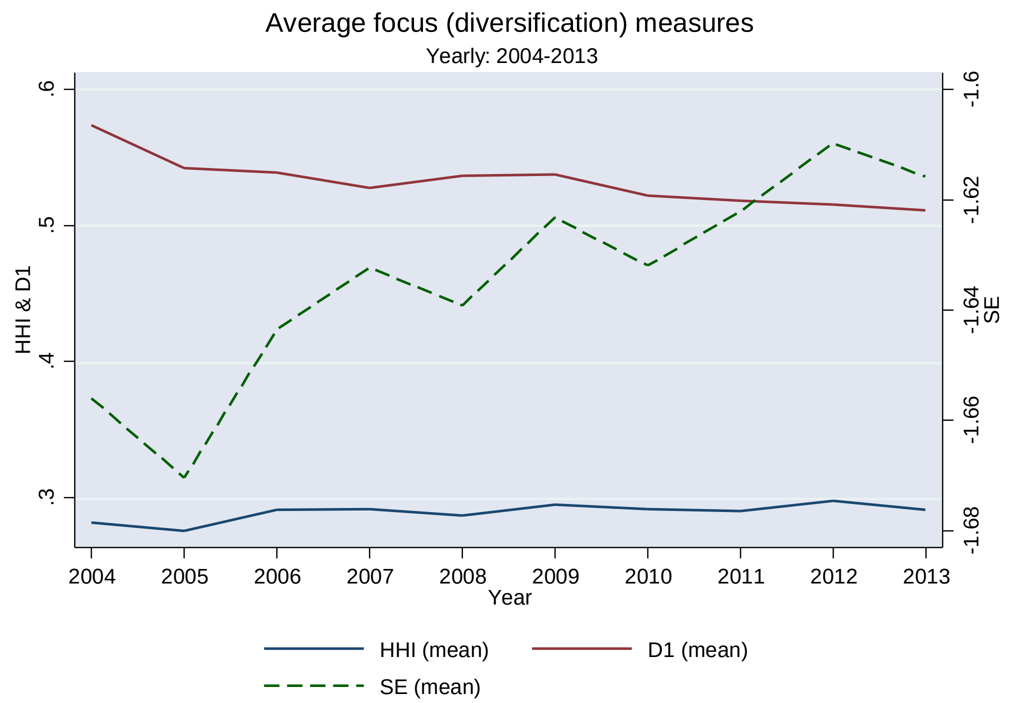

Figure 4

Note: Full sample HHI, D1, & SE 2004-2013

The relatively large standard deviations of the measures indicate substantial individual variations among banks, although the aggregate portfolio has been rather stable. Moreover, nearly the whole spectrum of possible degrees of diversification is captured in our sample as minimum and maximum values range from below 0.10 to 1. Banks with highly concentrated credit portfolios tend to be banks who specializes in consumer credit. These banks have all in common that their portfolio directed towards the business segment is dominated by loans made to other banks and credit institutions within the finance- and insurance category. However, the other side of the diversification-spectrum is more ambiguous with no particular type of banks overly represented. Furthermore, there are considerable individual portfolio adjustments undertaken over the period, although most are done at an already well-diversified level. For instance, Nordea has an HHI of 0.13 in 2004 and narrows its credit exposure every year until it reaches an HHI of 0.20 in 2012. Conversely, Sparebanken SMN is registered with an HHI of 0.25 in 2004 and gradually diversifies its portfolio down to an HHI of 0.16 in 2013.

Figure 5 shows the average portfolio composition over the sample period divided into the industry categories used in our analysis. Note that the composition shown in the chart is somewhat different than the one stated in the background section where the composition was defined according to Norges Bank's classification, and not the standard developed by SSB. However, regardless of which classification standard one uses, the main features of the aggregated portfolio will be the same.

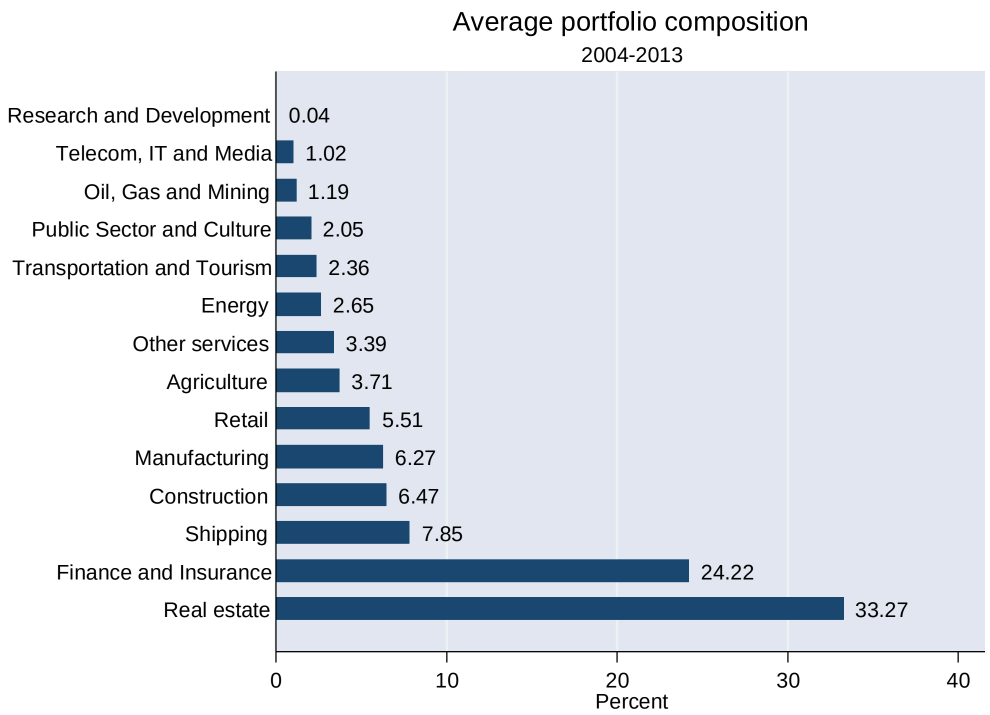

Figure 5

Note: Average aggregated portfolio composition of sample banks 2004-2013

The chart clearly illustrates the size of banks' exposure to the commercial real estate industry. Commercial real estate has been a highly preferred investment for banks, despite its vulnerability to economic downturns. At the beginning of the 2000’s and up to the crisis in 2008, loans made to firms in the real estate business grew rapidly with annual rates of 20% in both 2006 and 2007. The combination of low interest rates, booming economic activity and a general lack of available office spaces helped fuel the growth (Kredittilsynet, 2008). Real estate loans are also attractive for improving banks’ capital structure in response to higher capital requirements. When the risk of a bank’s capital stock is being assessed, mortgages and loans made for real estate purposes are given lower risk-weights than loans to other industries. Thus, banks can keep expanding their total credit portfolio by lending relatively more to these customers while still adapting to stricter capital requirements. To finance real estate lending, banks have increasingly chosen to engage in off-balance sheet activities and the sale of bundled real estate- and housing loans as covered bonds (OMF). The loans are transferred to a special purpose vehicle (SPV) controlled by the banks, and sold off to investors who have primary claim on the pool of loans if the issuer defaults on its obligations (Norges Bank, 2010). The OMF market has therefore become an efficient source of funding for banks since its introduction in 2007.

Given its dominating position in the Norwegian economy over the last decades, one would think that banks were more exposed to the oil and gas industry. A potential explanation may be the large presence of foreign oil and gas firms operating on the Norwegian continental shelf, which unfortunately are not included in our dataset. Moreover, some Norwegian oil and gas companies may choose to finance their operations in the bond market, which often offers better terms in the form of lower interest rates and more flexibility. In fact, companies operating in the oil and gas industry accounted for about 85 % of the outstanding amount in the Norwegian high-yield market in the period 2005-2011 (Bakjord & Berg, 2012). If a bank is exposed to the oil and gas industry through the bond market, it will occur as a financial asset on its balance sheet and not as a loan. Thus, banks may still be more exposed to oil and gas than our chart suggests, but as bond holders rather than via traditional loans.

Loans to financial- and insurance companies make up a significant share of the aggregated portfolio. A closer look at our data reveals that a majority of these loans are made to other banks contained in the dataset. Moreover, every firm that is registered as a holding company is classified as a finance- and insurance firm regardless of the classification of its subsidiaries. For instance, this means that a holding company with a subsidiary that operates in retailing is still categorized as a finance- and insurance firm, which thus increases the industry's share. Lastly, we see that the loans are fairly distributed among the remaining industries.

Looking at the broader picture, we see that banks in Norway are on average considerably diversified. The development over the 10-year period has been more or less stable, with a slight indication of higher diversification when measured by D1, and conversely increased concentration when considering SE. The industry as a whole, however, is more concentrated and is particularly exposed to the real estate industry.

7. Methodology and choice of estimation method

When dealing with panel data one has to do a qualified judgement of which estimation method that is best suited for the type of data one possesses and the purpose of the analysis. In contrast to basic cross-sectional and time-series data, which can be said to be one-dimensional, panel data allows you to utilize both the cross-sectional and time dimension in regression analyses. This unique feature makes panel data very suitable when wanting to control for unobserved effects that are thought to have an influence on the dependent variable but are not necessarily measurable. These unobserved effects can be divided into factors that are time-constant and those that vary over time (Wooldridge, 2014). In the context of a bank, time-constant factors might be bank-specific factors that impact a bank's return over a given period but are difficult to control for by including more independent variables in the model. Examples of bank-specific factors include the quality of the management and a bank's chosen business strategy. These factors, also called fixed effects, will vary across individual banks but are assumed to be constant and unique for each bank over a given period. Time-varying factors are factors that vary over time but do not vary across individual banks. Thus, the impact of changes in these factors are assumed to be common for all banks. One example is a macroeconomic shock that causes a shift in systematic risk, such as the financial crisis in 2008.

7.1 Fixed effects estimation

A great advantage of this estimation method is that it allows for correlation between unobserved effects contained in γ_b and the explanatory variables, $Cov(X_{btj,}\,\gamma_b) \neq 0\ t = 1,2 \ldots, T; j = 1,2 \ldots, k$. Hence, this estimation technique produces unbiased results even when such correlation is present. One drawback with this model is that it only utilizes time-variation within each individual bank and not across banks. As a consequence, an explanatory variable that do not vary over time will not be estimated (Wooldridge, 2014). This implies that the model will only have explanatory power if the variation above or below the mean of the dependent variable is sufficiently correlated with the variation above or below the mean of our explanatory variables.

7.2 Random effects estimation

In contrast to the fixed effects estimation, a random effects method can be applied when one can argue that the unobserved factors contained in the parameter γ_b is uncorrelated with the explanatory variables in all periods, $Cov(X_{btj,}\, \gamma_b) = 0\ t = 1,2 \ldots, T; j = 1,2 \ldots, k.$ This model thus allows us to estimate the effect of time-invariant independent variables in addition to the time-variation within each individual group. Consequently, this estimation method is more efficient than the fixed effect as this method utilizes more of the variation in our explanatory variables (Wooldridge, 2014)[3].

7.3 Choosing between fixed- and random effects estimation

The crucial point to consider when deciding between a fixed effects or a random effects method is whether or not our independent variables are likely to be correlated with the unobserved factors γ_b. It is plausible to assume that unobservable factors such as management proficiency and strategic decisions will affect measures of portfolio diversification, risk, level of administrative costs, and size. The zero-conditional mean assumption of OLS will then be violated, and the random effects estimation will produce biased results. One way to detect the potential presence of correlation is to perform a Hausman test. In the presence of correlation, the coefficients from the two estimation methods should be significantly different and the null hypothesis of zero correlation is rejected. After running the test, we reject the null hypothesis of no correlation which implies that the random effects estimator is not consistent. Thus, fixed effects estimation seems to be more suitable method for our analysis, which is in line with our original beliefs regarding correlation between unobserved factors and the independent variables we employ.

7.4 Autocorrelation and heteroskedasticity

The presence of autocorrelation and heteroskedasticity makes the test statistics and standard errors invalid, which consequently gives a false impression of the significance level of our independent variables. To investigate whether serial correlation is present, we perform a

[3] For a more thorough explanation of the fixed- and random effects estimation, see appendix 2.

Wooldridge test which tests for autocorrelation in panel data models. The result shows that we should reject the null hypothesis of zero autocorrelation. However, it should be noted that autocorrelation is only assumed to be an issue in long time series, typically over 20-30 years (Torres-Reyna, 2007). We also conduct a modified Wald test for groupwise heteroscedasticity where we reject the null hypothesis of homoscedasticity. Nevertheless, both these problems can be accounted for by running the regression with cluster-robust standard errors (Hoechle, 2007). This option corrects the standards errors and tests statistics to allow for heteroscedasticity and autocorrelation.

7.5 Final choice of estimation method: two-way fixed effects

The Hausman test indicates that our independent variables are correlated with the time-invariant bank-specific effects γ_b, which make fixed effects estimation preferable over random effects. However, as initially mentioned, Woolridge (2014) distinguishes between unobserved effects that are constant over time and those who varies across time. In addition to time-invariant bank-specific factors, common time-variant factors such as the financial crisis should be controlled for when examining the diversification-performance relationship. To account for possible time-varying factors, we extend our model by including year dummies, making it a two-way fixed effects model. Our final model thus looks as follows:

(3) $$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{5} \beta_n X_{nbt} + \gamma_b + \delta z_t + \varepsilon_{bt}$$

Where z_t represents a set of time dummies that controls for any policy changes or macroeconomic events that are common for all banks, but vary across time[4]. An implication of including year-dummies is that it requires some variation in the independent variables across banks within each time period. This implies that we cannot explicitly include variables such as the growth of GDP or interest rates that do not vary across banks. Thus, after thorough consideration we choose to investigate our research question by using a two-way fixed effects estimation with cluster-robust standard errors to correct for heteroscedasticity and autocorrelation.

[4] We find that the yearly dummies are jointly significant and are therefore included in our model.

8. Results

We start by analyzing the linear effect of portfolio diversification (concentration) on bank return when applying the loan loss rate and Z-score as risk measures. Then, in line with other comparable studies, we investigate whether there exists a non-linear relationship between portfolio diversification and return as a function of risk. To evaluate potential non-linear effects, we first use the non-linear model presented in section 4 before performing a robustness check by applying an interacted model using dummy variables for various levels of risk.

8.1 The average effect of diversification on return

8.1.1 Using loan loss as a proxy for risk

Table 3: Two-way fixed effects regression using loan loss as a risk measure

$$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{5} \beta_n X_{nbt} + \gamma_b + \delta z_t + \varepsilon_{bt}$$

Variables	1(a)	1(b)	1(c)	1(d)
$HHI_{\boldsymbol{bt}}$	-0.003*			-0.004**
	(0.002)			(0.002)
$D1_{bt}$		-0.001		
		(0.003)		
SE_{bt}			-0.001	
			(0.001)	
$Loan\ loss_{bt}$	-0.515***	-0.513***	-0.514***	-0.506***
	(0.046)	(0.047)	(0.047)	(0.050)
$Size_{bt}$	0.001	0.001	0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.004)
$Personnel_{bt}$	-1.263***	-1.272***	-1.266***	-1.313***
	(0.078)	(0.079)	(0.078)	(0.078)
$EQ - ratio_{bt}$				0.011
				(0.018)
Observations	1,094	1,094	1,094	1,094
Number of banks	112	112	112	112
Year dummies	YES	YES	YES	YES
Modified Wald test	0.000	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable represents the ratio of net income to total assets for bank b at time t, (ROA_{bt}). CM is the concentration measures HHI, D1, and SE for bank b at time t, respectively. Risk serve as the ratio of losses to gross lending for bank b at time t, ($Loan\ loss_{bt}$). The control variable X consists of size, personnel, and eq-ratio, which are defined as the logarithm of total assets, the ratio of personnel cost to total assets, and the ratio of equity to total assets for bank b at time t, respectively. γ_b represents the bank-specific time-invariant effects, while δz_t is the time year dummies. Finally, we include reported p-values of the Modified Wald test. Due to lack of space, the time dummies are not reported in the regression output.

Table 3 presents the results from the linear regressions where different concentration measures are regressed on banks' return on assets using loan loss as a proxy for risk. The estimated coefficients of the three concentration measures all turn out negative, although HHI_{bt} is the only one statistically significant on a 10% level. Note that the coefficient of HHI_{bt} is negligible higher in terms of absolute magnitude and still significant when we control for $EQ - ratio_{bt}$, while the coefficient of $EQ - ratio_{bt}$ itself is insignificant. As opposed to Hayden et al. (2006), there are no evidence suggesting that the amount of equity a bank holds is a reflection of its risk preference. Thus, we are more confident that the coefficients of HHI_{bt} actually captures the average effect on return. By looking at HHI_{bt}, there seems to be some evidence, though not very strong, that increased portfolio concentration on average tend to deteriorate bank returns. Additionally, the coefficients of loan loss are negative and highly significant, which suggests that there is no support of a positive relationship between bank return and risk. Riskier banks tend to experience lower returns on average. Interestingly, the insignificant $Size_{bt}$ variable reveals that there is no evidence of potential scale economies/diseconomies in the Norwegian banking market. One explanation can be that the effect of differences in bank size are already controlled for when removing fixed effects. The proxy for efficiency, $personnel_{bt}$, turns out negative and significant on a 1% level, which confirms the positive impact of increased efficiency on performance. The overall outcome of the variables of interest give some support of a positive relationship between bank return and increased diversification, given the assumption of a linear relationship.

8.1.2 Using Z-score as a proxy for risk

Table 4: Two-way fixed effects regression using Z-score as a risk measure

$$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{5} \beta_n X_{nbt} + \gamma_b + \delta z_t + \varepsilon_{bt}$$

Variables	2(a)	2(b)	2(c)	2(d)
HHI_{bt}	-0.004**			-0.004**
	(0.002)			(0.002)
$D1_{bt}$		0.000		
		(0.003)		
SE_{bt}			-0.001*	
			(0.001)	
$Z-score_{bt}$	0.036***	0.035***	0.036***	0.038***
	(0.006)	(0.006)	(0.006)	(0.007)
$Size_{bt}$	0.006	0.005	0.005	0.005
	(0.004)	(0.005)	(0.005)	(0.004)
$Personnel_{bt}$	-1.183***	-1.195***	-1.185***	-1.133***
	(0.063)	(0.062)	(0.062)	(0.132)
$EQ-ratio_{bt}$				-0.010
				(0.021)
Observations	1,094	1,094	1,094	1,094
Number of banks	112	112	112	112
Year dummies	YES	YES	YES	YES
Modified Wald test	0.000	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable represents the ratio of net income to total assets for bank b at time t, (ROA_{bt}). CM is the concentration measures HHI, D1, and SE for bank b at time t, respectively. Risk serve as the ratio of eq-ratio and return to the average st.deviation of return for bank b at time t, ($Z - score_{bt}$). Control variable X consists of size, personnel, and eq-ratio, which are defined as the logarithm of total assets, the ratio of personnel cost to total assets, and the ratio of equity to total assets for bank b at time t, respectively. γ_b represents the bank-specific time-invariant effects, while δz_t is the time year dummies. Finally, we include reported p-values of the Modified Wald test. Due to lack of space, the time dummies are not reported in the regression output. We choose to scale down the Z-score variable by 100 to make the coefficient more presentable.

Table 4 reports results where we employ Z-score as a proxy for risk. The results reveal that the coefficients of HHI_{bt} and SE_{bt} are both negative and significant on a 5% and 10% level, respectively. The coefficient of HHI_{bt} remains unchanged in terms of absolute magnitude and significance level when we control for $EQ - ratio_{bt}$, confirming our beliefs that the $EQ - ratio_{bt}$ is not determined by banks' risk preference. The coefficient of $D1_{bt}$ is still insignificant. In line with the previous results, there seems to be a positive relationship between increased diversification and banks' performance. Furthermore, an increase in Z-score, hence lower risk, has a significant positive impact on return, which thus substantiates the same risk-return relationship as indicated by the regression results presented in Table 3. The remaining control variables are similar to those in the estimations where we use loan loss as a proxy for risk.

Overall results from these linear estimations indicate that banks operating in Norway can benefit from shifts towards a more diversified credit portfolio, which supports the views held by Diamond (1984) and others within traditional banking theory. The results thus suggest that banks in our sample do not operate on the efficient frontier cf. portfolio theory, which implies that banks can change their risk-return profile through changes in portfolio diversification. Finally, the results from both linear regressions coincide, which makes us more confident about the robustness of our results.

8.2 The effect of diversification on return as a function of risk

8.2.1 Using loan loss as a proxy for risk

Table 5: Two-way fixed effects regression using loan loss as a risk measure

$$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{5} \beta_n X_{nbt} + \beta_6 CM_{bt} * Risk_{bt} + \beta_7 CM_{bt} * Risk_{bt}^2 + \gamma_b + \delta z_t + \varepsilon_{bt}$$

Variables	3(a)	3(b)	3(c)	3(d)
HHI_{bt}	-0.003*			-0.004**
	(0.002)			(0.002)
$HHI_{bt} * Loan\ loss_{bt}$	1.059**			1.111***
	(0.409)			(0.410)
$HHI_{bt} * Loan\ loss_{bt}^2$	-23.542***			-24.035***
	(8.043)			(8.466)
$D1_{bt}$		-0.002		
		(0.002)		
$D1_{bt} * Loanloss_{bt}$		1.062**		
		(0.520)		
$D1_{bt} * Loanloss_{bt}^2$		-13.472**		
		(5.895)		
SE_{bt}			-0.001	
			(0.001)	
$SE_{bt} * Loanloss_{bt}$			-0.024	
			(0.126)	
$SE_{bt} * Loanloss_{bt}^2$			1.570	
			(1.093)	
$Loan\ loss_{bt}$	-0.573***	-0.844***	-0.476**	-0.574***
	(0.112)	(0.279)	(0.223)	(0.109)
$Size_{bt}$	0.001	0.001	0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.004)
$Personnel_{bt}$	-1.222***	-1.228***	-1.261***	-1.280***
	(0.099)	(0.098)	(0.102)	(0.101)
$EQ - raio_{bt}$				0.014
				(0.016)
Observations	1,094	1,094	1,094	1,094
Number of banks	112	112	112	112
Year dummies	YES	YES	YES	YES
Modified Wald test	0.000	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable represents the ratio of net income to total assets for bank b at time t, (ROA_{bt}). CM is the concentration measures HHI, D1, and SE for bank b at time t, respectively. Risk serve as the ratio of losses to gross lending for bank b at time t, ($Loan\ loss_{bt}$). The control variable X consists of size, personnel and eq-ratio, which are defined as the logarithm of total assets, the ratio of personnel cost to total assets, and the ratio of equity to total assets for bank b at time t, respectively. γ_b represents the bank-specific time-invariant effects, while δz_t is the time year dummies. Finally, we include reported p-values of the Modified Wald test. Due to lack of space, the time dummies are not reported in the regression output.

Table 5 presents the results from the non-linear estimations when risk is proxied by loan loss. It should be noted that the interacted coefficients $Loan\ loss_{bt}$ and $Loanloss_{bt}^2$ represent the effect of concentration on return in respectively moderate and high risk scenarios, while the non-interacted concentration coefficients illustrate the effect of concentration on return when the risk level is low. The effect of changes in HHI_{bt} on return is significant for all risk scenarios, while the effect of changes in $D1_{bt}$ on banks' performance is significant in the case of moderate and high risk levels. SE_{bt} is insignificant for all risk levels and can thus not be given any meaningful interpretation. From the output we observe that the coefficients of our concentration measures HHI_{bt} and $D1_{bt}$ interacted with $Loan\ loss_{bt}$ and $Loanloss^2_{bt}$ are positive and negative, whereas the non-interacted concentration coefficients still hold a negative sign. This dynamic provides an inverted U-shape relationship between concentration and return as a function of risk. In order to get a better understanding of this U-shaped dynamic, we plot the prevailing relationship in Figure 6, which illustrates the marginal effect of changes in concentration measured by HHI on the return at different risk levels represented by loan loss[5].

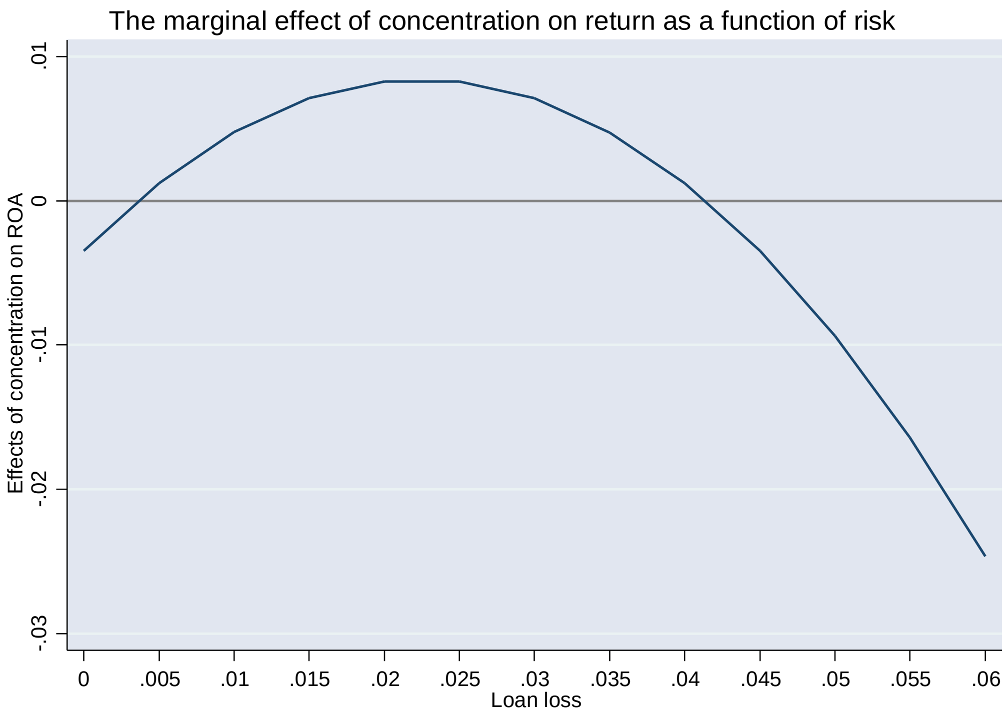

Figure 6

Note: Marginal effect of HHI on ROA for different risk levels

[5] We only plot the concentration measure which is significant at all risk levels.

The values of risk are expressed on the x-axis and ranges from 0% to 6,27%, which is the maximum loan loss rate in our sample period. The graph reveals that at the lowest levels of observed risk, the marginal effect of increased concentration has a negative impact on bank return (the curve is below 0). Knowing that the mean loan loss rate in our sample is 0,22%, we see that the average bank in Norway operates at low risk levels relative to the range of loan loss in our sample. Consequently, the effect of increased concentration will deteriorate return in the case of the average bank. As the degree of risk increases, the effect of increased concentration on banks' performance becomes less negative in magnitude and in fact turns positive at moderate risk levels relative to the observed risk in our sample (at approximately 0,4% loan loss). Finally, when the degree of risk exceeds 4%, the effect of increased concentration again deteriorates banks' return. It should be noted that this constitutes extreme risk levels (99^{th} percentile) compared to the sample median and mean of 0,14% and 0,22%. Nevertheless, there seems to be some evidence that banks operating in Norway should diversify their credit portfolios in both low and high risk scenarios in order to achieve increased returns. Further, the results suggest that banks may benefit from a more concentrated loan portfolio at moderate risk levels. These findings suggest that banks operating in Norway should assess the underlying risk level when determining the optimal strategy for their credit portfolio.

8.2.2 Using Z-score as a proxy for risk

Table 6: Two-way fixed effects regression using Z-score as a risk measure

$$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{5} \beta_n X_{nbt} + \beta_6 CM_{bt} * Risk_{bt} + \beta_7 CM_{bt} * Risk_{bt}^2 + \gamma_b + \delta z_t + \varepsilon_{bt}$$

Variables	4(a)	4(b)	4(c)	4(d)
HHI_{bt}	-0.025***			-0.027***
	(0.006)			(0.007)
$HHI_{bt} * Z - score_{bt}$	0.092***			0.104***
	(0.020)			(0.022)
$HHI_{bt} * Z - score_{bt}^2$	-0.063***			-0.073***
	(0.014)			(0.017)
$D1_{bt}$		-0.017***		
		(0.006)		
$D1_{bt} * Z - score_{bt}$		0.069***		
		(0.015)		
$D1_{bt} * Z - score_{bt}^2$		-0.050***		
		(0.011)		
SE_{bt}			0.001	
			(0.002)	
$SE_{bt} * Z - score_{bt}$			-0.015***	
			(0.004)	
$SE_{bt} * Z - score_{bt}^2$			0.016***	
			(0.004)	
$Z - score_{bt}$	0.033***	0.032***	0.046***	0.039***
	(0.006)	(0.008)	(0.010)	(0.007)
$Size_{bt}$	0.007	0.007	0.007	0.006
	(0.004)	(0.004)	(0.004)	(0.004)
$Personnel_{bt}$	-1.238***	-1.221***	-1.180***	-1.112***
	(0.050)	(0.047)	(0.057)	(0.126)
$EQ - ratio_{bt}$				-0.028
				(0.022)
Observations	1,094	1,094	1,094	1,094
Number of banks	112	112	112	112
Year dummies	YES	YES	YES	YES
Modified Wald test	0.000	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable represents the ratio of net income to total assets for bank b at time t, (ROA_{bt}). CM is the concentration measures HHI, D1, and SE for bank b at time t, respectively. Risk serve as the ratio of eq-ratio and return to the average st.deviation of return for bank b at time t, ($Z - score_{bt}$). The control variable X consists of size, personnel and eq-ratio, which are defined as the logarithm of total assets, the ratio of personnel cost to total assets, and the ratio of equity to total assets for bank b at time t, respectively. γ_b represents the bank-specific time-invariant effects, while δz_t is the time year dummies. Finally, we include reported p-values of the Modified Wald test. Due to lack of space, the time dummies are not reported in the regression output. We choose to scale down the Z-score variable by 100 to make the coefficients of interest more presentable.

When we apply Z-score as a proxy for risk, the coefficients of our concentration measures interacted with $Z - score_{bt}$ and $Z - score_{bt}^2$ represents moderate and low risk scenarios, respectively, since a high Z-score is associated with more financially robust banks. Hence, the coefficients of the non-interacted concentration measures represent the effect of changes in concentration on return at high risk levels. Both HHI_{bt} and $D1_{bt}$ are highly significant for all risk levels, and the associated signs give rise to the same dynamic as in the regressions reported in Table 5. SE_{bt} is significant in the case of moderate and low risk levels, and in fact suggests that increased concentration might have a positive impact on banks' performance in low risk scenarios. Nevertheless, when considering the effect of changes in portfolio concentration at all risk levels observed in our sample, the overall results are consistent with the ones where we interact concentration measures with loan loss. The marginal effect of changes in concentration on return as a function of Z-score is plotted in the figure below[6].

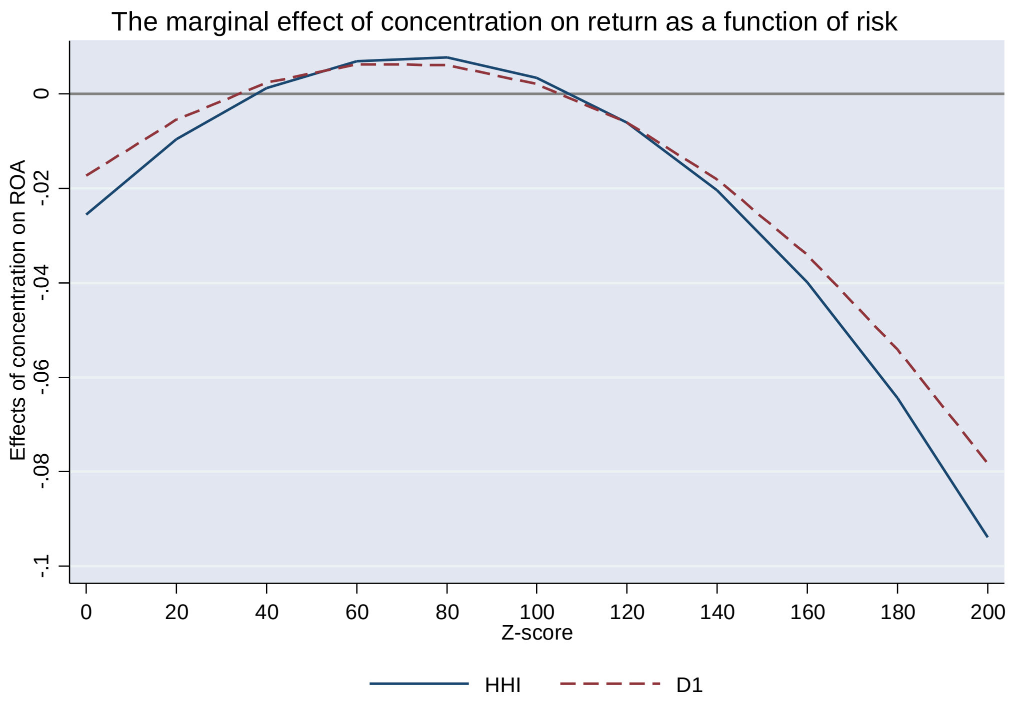

Figure 7

Note: Marginal effect of HHI & D1 on ROA for different risk levels.

At low risk levels relative to the range of Z-score in our sample (Z-score above 110), the effect of higher concentration will have an adverse impact on return. When the degree of risk is moderate (Z-score below 110), an increase in concentration results in a modest increase in bank return. In high risk scenarios (Z-score below 35), the effect of increased concentration again produces a reduction in return. These results coincide with the findings presented in

[6] We only plot the concentration measures which are significant at all risk levels.

Table 5 and thus strengthen the evidence of an inverted U-shape relationship between concentration and banks' performance as a function of risk.

Overall results from these non-linear estimations suggest that increased portfolio diversification seems to be the superior strategy for banks operating at low and high risk levels, whereas increased concentration appears to be the optimal strategy in moderate risk scenarios.

8.3 The effect of diversification on return as a function of risk: dummy approach

In order to investigate the potential non-linearity between portfolio concentration and banks' performance at different risk scenarios in further detail, we follow the examples of Acharya et al. (2006) and Hayden et al. (2006) and interact the concentration measures with dummy variables which represent various levels of risk:

$$Q_2 = 1 \text{ if } Risk^{[20]} < Risk_{bt} \leq Risk^{[40]} \text{ and zero otherwise}$$

$$Q_3 = 1 \text{ if } Risk^{[40]} < Risk_{bt} \leq Risk^{[60]} \text{ and zero otherwise}$$

$$Q_4 = 1 \text{ if } Risk^{[60]} < Risk_{bt} \leq Risk^{[80]} \text{ and zero otherwise}$$

$$Q_5 = 1 \text{ if } Risk_{bt} \geq Risk^{[80]} \text{ and zero otherwise,}$$

where $Risk^{[p]}$ is the p^{th} percentile of $Risk_{bt}$

8.3.1 Using loan loss as a proxy for risk

Table 7 presents the effect of changes in concentration on return where concentration measures are interacted with dummy variables representing different levels of loan loss. Note that the concentration variables and their associated coefficients which are not interacted with a dummy account for the impact of changes in portfolio concentration on return at the lowest risk level. Correspondingly, when examining the total effect of changes in concentration on banks' performance, the non-interacted coefficients serve as benchmarks and the interacted coefficients need to interpreted as deviations from these benchmarks (Hayden et al., 2006). To illustrate this, consider HHI_{bt} and $HHI_{bt} * Q_2$. The total impact of an increase in concentration on return when moving from the lowest risk level to Q_2 is still negative since the positive coefficient of $HHI_{bt} * Q_2$ is lower in magnitude than the negative coefficient of the benchmark, HHI_{bt}.

Table 7: Two-way fixed effects regression with interaction terms representing various levels of risk when using loan loss as a risk measure

$$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \sum_{k=2}^{5} \beta_k Q_{kbt} CM_{bt} + \beta_6 Risk_{bt} + \sum_{n=7}^{9} \beta_n X_{nbt} + \gamma_b + \delta z_t + \varepsilon_{bt}$$

Variables	5(a)	5(b)	5(c)	5(d)
HHI_{bt}	-0.007**			-0.007***
	(0.003)			(0.003)
$HHI_{bt} * Q_2$	0.003**			0.003**
	(0.001)			(0.001)
$HHI_{bt} * Q_3$	0.004**			0.004**
	(0.002)			(0.002)
$HHI_{bt} * Q_4$	0.006**			0.006**
	(0.003)			(0.003)
$HHI_{bt} * Q_5$	0.013***			0.013***
	(0.004)			(0.004)
$D1_{bt}$		-0.003		
		(0.003)		
$D1_{bt} * Q_2$		0.002*		
		(0.001)		
$D1_{bt} * Q_3$		0.002**		
		(0.001)		
$D1_{bt} * Q_4$		0.003**		
		(0.001)		
$D1_{bt} * Q_5$		0.006***		
		(0.002)		
SE_{bt}			-0.001	
			(0.001)	
$SE_{bt} * Q_2$			-0.000	
			(0.000)	
$SE_{bt} * Q_3$			-0.000	
			(0.000)	
$SE_{bt} * Q_4$			-0.000	
			(0.000)	
$SE_{bt} * Q_5$			-0.001***	
			(0.000)	
$Loan\ loss_{bt}$	-0.670***	-0.654***	-0.575***	-0.661***
	(0.071)	(0.063)	(0.046)	(0.077)
$Size_{bt}$	0.001	0.001	0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.003)
$Personnel_{bt}$	-1.254***	-1.283***	-1.280***	-1.300***
	(0.075)	(0.075)	(0.079)	(0.092)
$EQ - ratio_{bt}$				0.010
				(0.013)
Observations	1,094	1,094	1,094	1,094
Number of banks	112	112	112	112
Year dummies	YES	YES	YES	YES
Modified Wald test	0.000	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable represents the ratio of net income to total assets for bank b at time t, (ROA_{bt}). CM is the concentration measures HHI, D1, and SE for bank b at time t, respectively. Risk serve as the ratio of losses to gross lending for bank b at time t, ($Loan\ loss_{bt}$). The control variable X consists of size, personnel and eq-ratio, which are defined as the logarithm of total assets, the ratio of personnel cost to total assets, and the ratio of equity to total assets for bank b at time t, respectively. γ_b represents the bank-specific time-invariant effects, while δz_t is the time year dummies. Finally, we include reported p-values of the Modified Wald test. Due to lack of space, the time dummies are not reported in the regression output.

The results show that the coefficients of HHI_{bt} are significant for all risk scenarios, while the coefficients of $D1_{bt}$ are significant only when interacted with risk. The non-interacted coefficients of HHI_{bt} in 5(a) and 5(d) both turn out negative, suggesting that an increase in concentration at the lowest risk level results in lower returns. Furthermore, the positive magnitude of the interacted coefficients of HHI_{bt} and $D1_{bt}$ increases as we move towards higher risk levels, indicating that the overall adverse effect of higher concentration on return decreases as the risk reaches higher levels. In fact, the impact of increased portfolio concentration on banks' performance turns positive somewhere between risk levels Q_4 and Q_5, i.e. at moderate risk levels. To capture the point on the risk spectrum where increased concentration again deteriorates return, we would have to divide the percentiles into smaller intervals since these extreme risk levels are attributable to a relatively small number of banks (99^{th} percentile). Nonetheless, the pattern confirms to some degree the inverted U-shape relationship between increased concentration and bank return as a function of risk, where the benefits of a diversified portfolio are greater for low-risk banks than banks operating at higher risk levels.

8.3.2 Using Z-score as a proxy for risk

In Table 8 the various risk levels are represented by Z-score. The same interpretation of the coefficients as in the former dummy regressions applies in the estimations below. However, since we consider banks with a high Z-score to be low-risk banks, the risk spectrum is now inverted. Consequently, Q_5 represents banks operating at low risk levels, while the non-interacted concentration measures are applicable to high-risk banks.

Table 8: Two-way fixed effects regression with interaction terms representing various levels of risk when using Z-score as a risk measure

$$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \sum_{k=2}^{5} \beta_k Q_{kbt} CM_{bt} + \beta_6 Risk_{bt} + \sum_{n=7}^{9} \beta_n X_{nbt} + \gamma_b + \delta z_t + \varepsilon_{bt}$$

Variables	6(a)	6(b)	6(c)	6(d)
HHI_{bt}	-0.010***			-0.010***
	(0.004)			(0.004)
$HHI_{bt} * Q_2$	0.006***			0.006***
	(0.002)			(0.002)
$HHI_{bt} * Q_3$	0.010***			0.011***
	(0.003)			(0.003)
$HHI_{bt} * Q_4$	0.010***			0.010***
	(0.004)			(0.004)
$HHI_{bt} * Q_5$	0.008*			0.008*
	(0.004)			(0.004)
$D1_{bt}$		-0.003		
		(0.003)		
$D1_{bt} * Q_2$		0.004***		
		(0.001)		
$D1_{bt} * Q_3$		0.005**		
		(0.002)		
$D1_{bt} * Q_4$		0.005*		
		(0.003)		
$D1_{bt} * Q_5$		0.003		
		(0.003)		
SE_{bt}			-0.001	
			(0.001)	
$SE_{bt} * Q_2$			-0.001***	
			(0.000)	
$SE_{bt} * Q_3$			-0.001**	
			(0.001)	
$SE_{bt} * Q_4$			-0.001	
			(0.001)	
$SE_{bt} * Q_5$			-0.001	
			(0.001)	
$Z - score_{bt}$	0.034***	0.034***	0.035***	0.036***
	(0.006)	(0.007)	(0.007)	(0.008)
$Size_{bt}$	0.006	0.005	0.006	0.005
	(0.005)	(0.005)	(0.005)	(0.004)
$Personnel_{bt}$	-1.190***	-1.198***	-1.188***	-1.122***
	(0.059)	(0.059)	(0.061)	(0.134)
$EQ - ratio_{bt}$				-0.014
				(0.020)
Observations	1,094	1,094	1,094	1,094
Number of banks	112	112	112	112
Year dummies	YES	YES	YES	YES
Modified Wald test	0.000	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable represents the ratio of net income to total assets for bank b at time t, (ROA_{bt}). CM is the concentration measures HHI, D1, and SE for bank b at time t, respectively. Risk serve as the ratio of eq-ratio and return to the average st.deviation of return for bank b at time t, ($Z - score_{bt}$). The control variable X consists of size, personnel and eq-ratio, which are defined as the logarithm of total assets, the ratio of personnel cost to total assets, and the ratio of equity to total assets for bank b at time t, respectively. γ_b represents the bank-specific time-invariant effects, while δz_t is the time year dummies. Finally, we include reported p-values of the Modified Wald test. Due to lack of space, the time dummies are not reported in the regression output. We choose to scale down the Z-score variable by 100 to make the coefficients of interest more presentable.

The table depicts that the impact of changes in HHI_{bt} is significant for all risk levels. Moreover, the coefficients of HHI_{bt} and $D1_{bt}$ exhibit the same prevailing dynamic as the estimations presented in Table 7, although the effect of changes in $D1_{bt}$ turns out significant only at moderate risk levels. In contrast to the results in the previous subsection, we manage to capture the entire inverted U-shape relationship between concentration and bank return when the risk is represented by Z-score; when considering the results from 6(a) and 6(d), we see that the values of $HHI_{bt} * Q_2$ and $HHI_{bt} * Q_5$ are lower in positive terms than the negative magnitude of the benchmark coefficients HHI_{bt}. However, at risk levels Q_3 and Q_4 (moderate risk levels) the positive value of the interacted concentration coefficients are slightly higher than the negative value of the benchmarks[7]. Thus, these estimations show that the adverse effect of increased concentration on banks' performance decreases as the risk approaches moderate levels. In line with our former findings, these results suggest that banks operating at moderate risk levels should consider a more concentrated credit portfolio in order to achieve higher returns. In addition, the results from regression 6(a) and 6(d) indicate that increased diversification appears to be advantageous for low and high-risk banks. These estimations therefore further strengthen our previous findings of an inverted U-shape relationship between concentration and bank performance as a function of risk.

Overall findings from these dummy-approach regressions are consistent with the results from our non-linear models presented in Table 5 and 6 and confirms the hypothesis that the effect of changes in portfolio diversification (concentration) on banks' performance is dependent on the underlying bank risk.

8.4 Further analysis – isolating the business segment

The financials we use in our analysis report aggregate figures from all business activities conducted by each bank. Since household loans represent half of banks' total loan at the aggregated level, while approximately 35% of banks' total assets are related to other activities than lending, our performance and risk variables will contain elements of return and risk generated from other operations than commercial lending. As an extension of our main

[7] The coefficients of $HHI_{bt} * Q_3$ and $HHI_{bt} * Q_4$ in the regression output 6(a) gives the value 0.0104 when adding one additional decimal, whereas the coefficient of HHI_{bt} is -0.0101. Moreover, the coefficients of HHI_{bt} and $HHI_{bt} * Q_4$ in 6(d) are respectively -0.0097 and 0.0104 when adding one additional decimal.

research question, we choose to perform an additional analysis where we isolate the income streams and credit risk generated from activities related to commercial lending. The purpose of this analysis is therefore to isolate the business segment and investigate whether the prevailing diversification-performance relationship found in our primary analysis holds when removing elements of risk and return stemming from other activities than commercial lending. This analysis can thus be viewed as a robustness check, and coinciding results will be interpreted as a further strengthening of the reliability of our previous findings.

To obtain relevant financial data, we have gone through annual reports for 12 of the largest saving banks in our main sample over the period 2004-2013 and gathered return and loss figures related to the business segment. It should be noted that detailed segment information is not always published and that we choose to include the 12 largest saving banks where this information is available. Furthermore, for some banks segment information is not accessible for all years. Thus, our final subsample consists of 12 saving banks and 107 observations over the time span 2004-2013, and constitutes a combined market share in lending of about 20%[8].

In this analysis we apply our main diversification measure HHI_{bt} and we define ROA_{bt} as the ratio of net income to total assets related to the business segment. Correspondingly, $loan\ loss_{bt}$ represents losses incurred in commercial lending as a share of total assets in the business segment. Note that virtually all assets in the business segment are comprised of loans. In order to determine which econometric method to use, we perform a Hausman test in which we fail to reject the null hypothesis of zero correlation between the independent variables and the unobserved factors γ_b. As a result, we perform a random effects estimation as this method is proven to be more efficient than fixed effects[9]. Finally, we use robust standard errors to correct for the presence of heteroscedasticity and autocorrelation. The results are presented in Table 9 below.

[8] In order to examine whether the selected banks are a representative sample of the banks contained in our main sample, we regress the relevant variables on the return of these selected banks when all sources of risk and return are considered. The result from this regression exhibits the same negative relationship between increased portfolio concentration and return as found in our main analysis. The selected banks can thus be viewed as a representative subsample. An overview of our subsample can be found in appendix 3.

[9] See appendix 2 for a more detailed explanation of the random effects model.

Table 9: Two-way fixed- and random effects regression using loan loss as a risk measure

$$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{4} \beta_n X_{nbt} + \delta z_t + v_{bt}$$

$$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{4} \beta_n X_{nbt} + \beta_5 CM_{bt} * Risk_{bt} + \beta_6 CM_{bt} * Risk_{bt}^2 + \delta z_t + v_{bt}$$

	Random effects		Fixed effects	
Variables	7(a)	7(b)	7(c)	7(d)
HHI_{bt}	-0.037**	-0.034**	-0.046*	-0.040*
	(0.015)	(0.014)	(0.022)	(0.021)
$HHI_{bt} * Loan\ loss_{bt}$		0.030***		0.029**
		(0.008)		(0.010)
$HHI_{bt} * Loan\ loss_{bt}^2$		-0.011*		-0.010
		(0.006)		(0.006)
$Loan\ loss_{bt}$	-0.827***	-0.012***	-0.818***	-0.012***
	(0.177)	(0.003)	(0.174)	(0.003)
$Size_{bt}$	-0.004*	-0.004*	0.002	0.002
	(0.002)	(0.002)	(0.005)	(0.005)
$Personnel_{bt}$	-0.144	-0.100	0.395	0.401
	(0.848)	(0.878)	(0.992)	(1.036)
Observations	107	107	107	107
Number of banks	12	12	12	12
Year dummies	YES	YES	YES	YES
Modified Wald test			0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable represents the ratio of net income to total assets related to the business segment for bank b at time t, (ROA_{bt}). CM is the concentration measure HHI for bank b at time t. Risk serve as the ratio of loan losses to total assets related to the business segment for bank b at time t, ($Loan\ loss_{bt}$). The control variable X consists of size and personnel which are defined as the logarithm of total assets, and the ratio of personnel cost to total assets for bank b at time t, respectively. γ_b represents the bank-specific time-invariant effects, while δz_t is the time year dummies. Finally, we include reported p-values of the Modified Wald test. Due to lack of space, the time dummies are not reported in the regression output. We choose to scale up the loan loss variable by 100 when employing the non-linear models to make the coefficients of interest more presentable. We fail to reject the null hypothesis when using the Hausman test. Nevertheless, we present both the fixed- and random effects model.

When considering the linear regression 7(a), we see that the HHI_{bt} coefficient is statistically significant and negative, which is in line with the findings in Table 3 and 4. Given a linear relationship between return and diversification, increased concentration seems also to have a negative impact on banks' return when focusing merely on the business segment. Thus, increased industrial diversification appears to contribute positively to banks' performance. Next, following the analysis conducted in Table 5 and 6, we investigate whether there exist any nonlinearities between diversification and return as a function of risk. Results from these estimations are presented in column 7(b) and 7(d). The results from the random effects regression reveal that all the HHI_{bt} coefficients are statistically significant and display the same non-linear relationship as found in the primary analysis (see Table 5 and 6). Also note that the coefficient of $Size_{bt}$ is negative and significant on a 10% level when we employ the random effects estimation, which may indicate that larger banks tend to be less efficient. This underpins our assumption that effect of differences in bank size are eliminated when controlling for fixed effects. The marginal effect of changes in HHI_{bt} on return for different risk levels is plotted below.

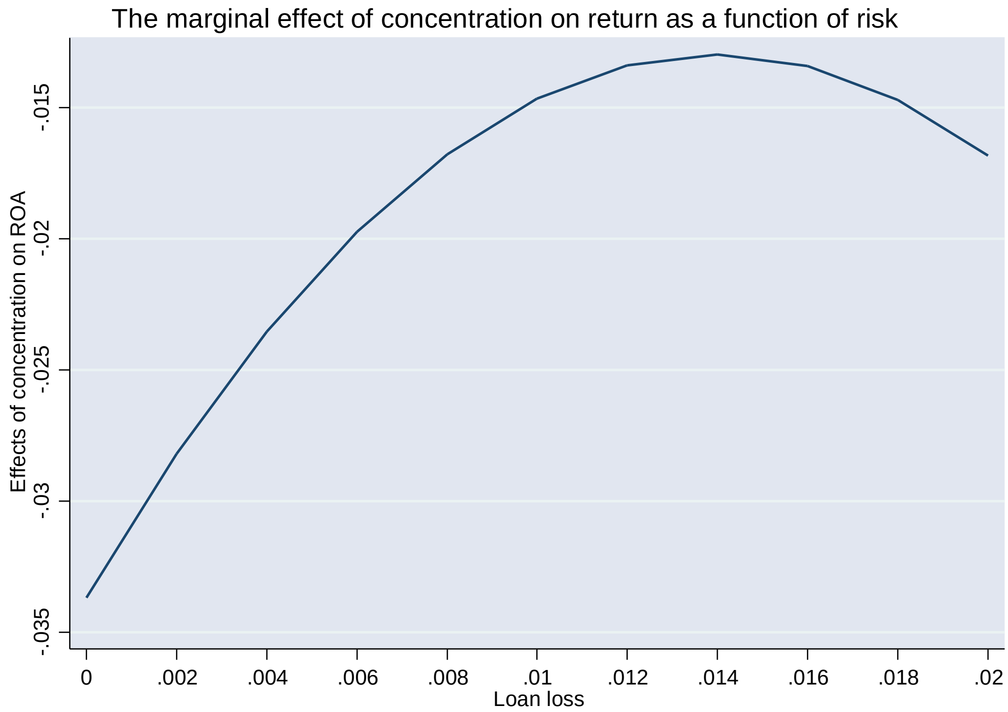

Figure 8

Note: Marginal effect of HHI on ROA for different risk levels. The figure is based on the results from 7(b).

Interestingly, the effect of increased concentration never turns positive, which indicates that a diversified credit portfolio will be superior at all points on the risk spectrum. However, the figure illustrates that the positive effect of increased diversification decreases as risk moves towards moderate levels (the adverse effect of increased concentration becomes less negative). This effect is reversed when risk exceeds a certain threshold. Although increased portfolio concentration does not improve bank performance at any of the risk levels observed in our subsample, the results exhibit the same inverted U-shape relationship. The results from this analysis thus give us further evidence of a positive effect of increased diversification on bank performance, and suggest that banks operating in Norway should assess the underlying risk when choosing the optimal strategy for their credit portfolio.

To sum up, overall findings show that our results are consistent even when different variables are applied to capture risk and portfolio concentration. All estimations point in the direction of deteriorated bank returns as portfolio concentration increases, given a linear relationship between portfolio concentration and banks' performance. Moreover, results from different estimation techniques and model specifications indicate that banks should consider the underlying risk when choosing the optimal diversification strategy for their commercial credit portfolio. The potential financial benefit of portfolio adjustments in terms of changes in diversification seems to be highly dependent on risk. In order to improve bank performance, our results suggest that increased concentration is beneficial for banks that operate at moderate risk levels, while a more diversified credit portfolio seems to be favourable for both low and high-risk banks. However, results from our subsample indicate that higher concentration lessens bank returns in all risk scenarios, where the negative impact decreases in magnitude as the risk approaches moderate levels. Consequently, the overall findings from our non-linear estimations suggest that the effect of portfolio diversification is contingent on the underlying risk, which is in line Winton's (1999) theory. However, the interaction between concentration, risk, and return for banks in Norway is in contrast with his hypothesis of a U-shaped relationship.

Now, the question of why the Norwegian banking market exhibits an entirely opposite dynamic than the one found by for example Acharya et al. (2006) and Hayden et al. (2006) in Italy and Germany, is highly interesting and opens the door for further investigation on this topic. They found evidence in support of Winton's (1999) hypothesis of a U-shaped relationship between increased concentration and return as a function of risk. The scope of this research question requires careful considerations and are beyond the topic of our thesis. In the next section, however, we will nonetheless briefly point out some structural differences that we believe should be considered when trying to explain the contrasting results. We choose to emphasize on Italy and Germany given the fact that these are considered to be advanced countries with well-developed financial systems, which will make the comparison to Norway more suitable. This discussion is based on our knowledge acquired throughout the research process and will hopefully contribute to lead future researchers in the right direction.

9. Potential sources of divergence

The diversification-performance relationship is likely to be affected by the underlying market structure within each country, both in terms of how the banking sector is organized as well as the economy in general. Factors such as bank ownership, distinctive regulations, competition, and industrial structure are expected to affect banks' strategic positioning in addition to the level of risk and profitability. Thus, differences in the interaction between diversification, risk, and return are likely to be contingent on fundamental characteristics of the market. Such differences have to be considered when trying to explain why our results differ from similar studies done in other countries. Moreover, a country's economy and banking sector are not stationary, but rather dynamic processes that evolve as new technology, industries, and regulations develops. This means that the results of such a study have to be interpreted in light of the particular sample period. As a consequence, we focus on market traits around the period of when the comparable studies were performed as well as more recent developments.

9.1 Market characteristics

The German financial system is firstly characterized as being bank based rather than capital market based, meaning that the share of total banking assets to GDP is relatively high whereas total stock market capitalization as a ratio of GDP is lower compared to other developed countries. Secondly, the banking sector is highly fragmented with large state influence (Hüfner, 2010). The German banking sector is organized in three so-called pillars; commercial, savings, and cooperative. All three pillars are universal, meaning that they are permitted to collect deposits, issue loans, and engage in trading activities on behalf of customers as well as for their own account (Koetter, 2013). Also, a sub-pillar consisting of specialized mortgage banks are active in the housing market. Although the three main pillars have been granted similar permissions, they differ in terms of ownership, size, geographical orientation, and main operations.

Most commercial banks in Germany are privately owned, although only a few are publicly listed. These banks are often larger in size than banks in the other pillars and operates across regional as well as national borders. In terms of operations, they tend to be more active in investment banking and are often the preferred banks for larger domestic and international companies. The share of aggregated bank assets held by commercial banks grew from 14% in

1993 to 37% in 2012 (Koetter, 2013). Factors such as open borders, financial sector deregulation, and the introduction of a common European currency are all plausible explanations for the reinforced position of commercial banks. In Norway, excluding the subsidiaries and branches of large foreign commercial banks, DNB is assumable the only bank with comparable characteristics, albeit with a highly dominant position.

The regulation and characteristics of German saving banks differ to a large extent from saving banks in Norway. While Norwegian saving banks are free to compete across regions and to organize as private limited companies, saving banks in Germany face regional demarcation and are in addition owned by local government bodies such as municipalities. Together these state-owned saving banks own Landesbanken, which is the head banking institution for saving banks within each region. Landesbanken thus functions as a clearing house for local and regional saving banks in a particular area (Koetter, 2013) . Given their status as publicly owned entities, these banks are obliged to follow distinctive national and state banking laws according to a principle of serving the public good, which puts profit maximization not as a primary objective. Furthermore, prior to 2002, Landesbanken and saving banks within the public system enjoyed a bailout guarantee given by the government in the case of insolvency. After strong objections from private banks and the European Commission, the promise of bailout was partly abolished in 2002. Although the bailout guarantee was abolished, all deposits were still to be guaranteed by the government (Hüfner, 2010).

According to Hüfner (2010), the German public banking system owned about 40% of total banking assets prior to the financial crisis in 2008-2009. The significant public influence and following dissimilar regulatory framework met by private and public banks are likely to shift the competitive dynamic of the banking market. The mere fact that 40% of the banking assets are not utilized for the purpose of increasing profits raises question about the degree of efficiency in the sector. A non-profit banking system where banks are exempt the risk of bankruptcy and the incentive to improve their operations for monetary rewards are likely to cause distortions in terms of competition and ultimately lead to inefficiencies. Additionally, a non-profit banking system backed by governmental guarantees are likely to have an adverse effect on banks' incentive to monitor its borrowers, which may increase problems of moral hazard in the form of more excessive risk-taking by customers, and hence higher losses for banks. Although the Norwegian banking market has a large share of saving banks, nearly the only things they have in common with German saving banks are their tendency of local orientation and the forms of services they provide. In terms of ownership, organizational structure, the basis for incentives, competitive environment, and regulatory framework in which they operate, the two can hardly be compared. The influential position of saving banks and their uniqueness contributes to differentiate the German banking sector from a more liberal and deregulated banking sector such as the one in Norway. It should be noted, however, that the Norwegian government has some influence besides regulatory enforcement through its stake in DNB. Nevertheless, these fundamental differences in market structure may cause a shift in the relationship between diversification, risk, and profitability, which lead to the findings of Hayden et al. (2006). Again, it is important to specify that they used annual data for the period from 1996 to 2002, which implies that a similar study done with data from a later period may have given other results. However, to the best of our knowledge, the main features of the German banking sector during that period are still present.

Similar to Germany, the financial system in Italy is dominated by banks. In 2012, banks controlled about 85% of total assets in the financial sector. The Italian economy is mostly composed of small and medium sized firms, where banks play an important role as their main source of funding. The banks are divided into three categories; private joint stock companies, small mutual banks, and cooperatives. All Italian banks are for-profit, except the small mutual banks. Banks organized as private joint stock companies accounted for 70% of total banking assets in 2012. Despite this, the banking market in Italy is highly fragmented and are in fact the European country with most branches per capita. Out of a total of 706 banks, 394 were categorized as small mutual banks in 2012. Although being large in number, these banks controlled only 6% of total banking assets (IMF, 2013). The large share of private ownership and profit-oriented banks is in contrast to the German system and draws more similarities to the one in Norway. However, it is important to emphasize that during the sample period used by Acharya et al. (2006), 1993-1999, the Italian banking sector underwent a process of restructuring consisting of state-ownership divestment and consolidation. This implies that a significant share of their sample banks either was state-owned during the whole sample period or underwent a process of privatization. In fact, out of 105 banks in their sample, only 34 were classified as private. Being aware of this, the authors performed a robustness check where they used a subsample consisting of these 34 private banks and concluded that their main findings remained unaffected. Although the effect of diversification remained unchanged when they excluded the state-owned banks, this does not discredit our beliefs about the relationship between return, risk, and diversification being affected by the market structure and economic environment in which banks operate. The fact that these private banks operated in a highly state-controlled environment raise the same concerns regarding market dynamics as pointed out in the case of Germany.

9.2 Portfolio composition and risk

In the background section, we pointed out that about 65% of total banking assets in Norway consist of loans made to commercial and private customers. When we include loans to other financial firms, including banks, total loans to assets are approximately 75%. In comparison, customer loans excluding interbank loans made up on average 45% of total assets of German banks in the period 1993-2012. Moreover, loans made between banks amounted to 22% of total assets (Koetter, 2013). The relatively small share of traditional loans has been amplified during years after the financial crisis due to regulations imposed by the third Basel accord. To meet higher capital requirements, banks can either retain a larger share of their earnings, issue new equity, or shrink their balance sheets. The latter implies that banks become more reluctant to make new loans, which are in fact what has happened in Germany in the post-crisis years. The reduction in loans supplied by banks has led to a boom in the corporate bond market, especially for small and medium sized firms who have been hardest hit by banks' tightening of credit supply (Kaya & Meyer, 2013). The share of customer loans excluding interbank loans has thus decreased to 32% in 2017, according to data made public by the European Central Bank (ECB). The difference in asset composition may indicate that a smaller share of German banks' return stems from traditional lending activities compared to banks in Norway. This also applies for the overall risk. Data from the Italian banking sector shows that the ratio of loans to commercial and private customers to total assets was 53% in 2010, and 66% when we include interbank loans (De Bonis, Pozzolo, & Stacchini, 2012).

The significant exposure to households and the housing market in particular has been a growing concern for regulatory authorities in Norway. Loans to households, where mortgages being the dominating asset class, amounted to about 33% of total bank assets in 2013. In Germany and Italy, however, the ratio was respectively 17% and 16% in 2010 (De Bonis et al., 2012). Much can be explained by cultural differences in regard to renting versus home ownership, in addition to differences in relative housing prices. The owner occupation rate in Norway was on average 84% during our sample period and respectively 53% and 73% in Germany and Italy over the same time span. This also manifests itself in overall debt levels for households; residential loans as a share of disposable income for households in the three countries was in the same period 134% (Norway), 70% (Germany), and 27% (Italy). In fact, Norway has by far the largest amount of residential loans per capita when compared to any of the 28 countries in the European Union (European Mortgage Federation, 2014). These fundamental differences will are likely to affect the general risk profile of the average bank in the countries.

Even though the large share of loans to households in Norway are considered to be an amplifier of systemic risk, household lending is still associated with lower risk in terms of loan losses compared to commercial lending. According to Jahn, Memmel, and Pfingsten (2013), the average loan loss for German banks was about 1,3% of total loans in the period 2003-2011, whereas loan losses in Norway have been consistently below 0,5% since the end of the banking crises in the early 1990's (Kragh-Sørensen & Solheim, 2014). The lower loss rate in Norway can certainly not be attributed to the larger share of household lending alone since general economic conditions play an important role, but it may serve as one of several explanatory factors. We can nevertheless assert that the general risk level, measured by losses, in the German lending market has historically been higher than in Norway. The issue of loan losses and non-performing loans has in particular been evident in Italy and has been amplified in the aftermath of the 08/09-crisis. The share of non-performing loans has tripled since the beginning of the crisis and reached 18% of total outstanding loans in the end of 2015 (Garrido, Kopp, & Weber, 2016). In comparison, non-performing loans to corporations and households in Norway were 0,40% and 0,48% of total loans in 2015 (Norges Bank, 2015). According to Garrido et al. (2016), highly indebted corporations, a sharp decline in output after the crisis, low bank capital buffers, and a complex and inefficient legal system for corporate restructuring have all been contributing factors to the high level of non-performing loans in Italy. It is worth noting, however, that during the sample period of the study done by Acharya et al. (2006) the sample average of non-performing loans was 5,2%. Nevertheless, the overall risk in the Italian banking market is perceived to be relatively high and has been given much attention from financial spectators the recent years. To ensure financial stability, the need for structural reforms and consolidation of the banking sector has particularly been emphasized. Given the higher level of credit risk associated with lending in these countries, one may assume that industry-specific knowledge is a more decisive element in the lending process. Thus, a more concentrated portfolio can be beneficial for improving screening- and monitoring efficiency.

An indicator which is carefully watched by investors and market participants when assessing the risk and soundness of a financial institution is the so-called credit default swap spread

(CDS). A CDS is essentially an insurance contract where the buyer of the swap makes payments to the seller up until maturity in exchange for credit protection in the event of default of an underlying security, which often is a fixed income security such as a bond issued by a corporation or a financial institution. If the debt-issuer defaults on its payments, the seller of the CDS will pay the bond's face value to the buyer of the swap. The CDS spread in this context is the premium a seller charges a buyer to guarantee the buyer against a credit event and thus reflects the market's perceived credit risk of a particular bond issuer. Ballester, Casu, and González-Urteaga (2016) collected daily spreads on 5-year CDS for European and US banks with actively traded CDS in the period January 2004 to March 2013. The average spread for the seven largest Italian banks was 157 basis points, whereas the spread for the four largest German banks was 87 basis points. DNB, as the only Norwegian bank with frequently traded CDS in the sample period, had an average spread of 100 basis points. As the European sovereign debt crisis evolved in 2009, the spread for Italian banks surged. The average spread for the four largest Italian banks during October 2009 to March 2013 was 303 basis points, with the highest observed spread for an individual bank reaching 694 basis points. The average spread for German and Norwegian banks in the same period was 144 and 99, respectively. More recent developments in both the Italian and German banking sector have once again made experts question the soundness of the financial systems in these countries. After a series of bad news and a proposed fine of $14 billion for mis-selling mortgage-backed securities, the stock price of Germany's largest bank, Deutsche Bank, fell dramatically during the autumn of 2016 (Bloomberg, 2016). At the same time, the world's oldest and Italy's fifth largest bank, Monte dei Paschi di Siena, had to be bailed out by the Italian government in a $20 billion recapitalization package (Financial Times, 2016).

It is difficult to know exactly how these differences in market structure, asset composition, and risk affect the relationship between bank returns, diversification, and risk other than recognizing them as features worth looking into when trying to explain the contrasting dynamic. It is, nonetheless, evident that the German banking market is heavily influenced by a strong governmental presence, which was also true for the Italian market during the sample period used by Acharya et al. (2006). When comparing the asset composition of banks in the three countries, we see that both German and Italian banks are more engaged in other activities than traditional banking and less exposed to households and the real estate market. This means that a larger share of risk and revenue-generating assets is not related to traditional lending. Moreover, the credit risk associated with lending, measured by loan losses and non-performing loans, are significantly higher in both countries relatively to Norway. In addition, the perceived credit risk of the banks supplying the credit also tends to be higher, which implies that both the demand and supply side of credit operates at higher risk levels. This, in turn, is likely to be a reflection of the general economic conditions in the countries. Considering the different economic environment in which Norwegian banks operates, the basis for making a meaningful comparison with these studies seems at best dubious.

10. Concluding remarks

In this master thesis, we have examined the effect of industrial portfolio diversification on banks' performance when measured by return on assets. By utilizing a unique dataset composed of individual bank loans, we analyzed the diversification-performance relationship for 112 banks in Norway over the sample period 2004-2013. Using different econometric analysis and methodological approaches, we have demonstrated that banks' choice of diversification strategy has a significant impact on profitability. While scholars such as Denis et al. (1997) and Mishkin et al. (2013) within corporate finance theory claim that the optimal portfolio strategy for enhancing performance and countering agency problems is to concentrate on operations in which banks possess expertize, we find no empirical evidence for this assertion in the Norwegian banking market. In fact, our findings are consistent with the views held by Diamond (1984) and others within traditional banking theory who base their arguments on improved monitoring incentives, and hence improved performance, as banks become more diversified. Our results clearly show that the average effect of increased portfolio concentration seems to deteriorate bank profitability. Moreover, this result is consistent across different measures of diversification.

However, by merely focusing on a linear relationship between diversification and profitability one may underestimate the importance of risk in banks' strategic portfolio decision and thus oversimplify the analysis. In this regard, Winton (1999) presents a theory where he argues that the effect of diversification on bank profits is contingent on the level of risk. After having employed several estimation techniques to test this assertion, we find consistent evidence in support of a non-linear relationship between diversification and return in bank risk. Despite these results, our findings coincide with Winton (1999) only in the issue of risk contingency. According to him, the relationship between increased portfolio concentration and return at different risk levels is assumed to be non-linear and U-shaped, whereas our analysis suggests an inverted U-shaped relationship. For our sample banks, this implies that increased diversification seems to be the superior strategy in low and high risk scenarios, while higher portfolio concentration tend to be beneficial at moderate risk levels. To further investigate this issue, we performed a robustness check where we isolated the risk and return generated in the business segment for 12 of the banks in our main sample. Although the effect of increased concentration never contributes positively to banks' return, we find the same inverted U-shaped relationship as in the primary analysis. Conversely, comparable studies performed in other developed countries such as Italy and Germany find evidence of a diversification-performance relationship in favour of higher portfolio concentration. Results from Acharya et al. (2006) and Hayden et al. (2006) show that the average effect of increased industrial concentration has a positive impact on the return of Italian and German banks. In addition, their findings are consistent with Winton's (1999) hypothesis of a U-shaped relationship between increased concentration and return as a function of risk. Given the contrasting results of our study compared to the findings in these developed countries, we propose a set of potential explanations by emphasizing differences in underlying factors such as market structure and general economic conditions. This discussion reveals fundamental differences between the countries in terms of bank ownership, regulations, levels of risk, etc. We argue that these differences should be accounted for in order to make meaningful comparisons.

The recent financial crisis illustrated the acute economic consequences of a failing financial system. Although the contributing factors were complex, evidence suggests that banks' large exposure to the housing market helped amplify the severity of the crisis. Banks' strategic portfolio decision is thus highly important from a policy point of view when trying to mitigate systemic risk in order to ensure financial stability. Our findings show that when preparing regulatory frameworks encouraging banks either to specialize or diversify their credit portfolios, policymakers should assess the underlying risk. However, the prevailing dynamic of the diversification-performance relationship is seemingly ambiguous and has to be considered in light of country-specific factors. At last, we encourage others to continue the work we began by investigating these factors in further detail and examine what factors cause the dynamic to shift and in what way. Increased knowledge about this topic will enable bank managers and regulators to make more informed decisions and as a result contribute to financial stability and sound economic development.

Appendix 1: An overview of our main sample

The table below presents the sample banks and their average total assets in the sample period

	Banks	*Size (in mill.)*		*Banks*	*Size (in mill.)*
1.	DNB	*1 327 681*	**31.**	LILLESTRØM SPAREBANK	*5 139*
2.	NORDEA BANK NORGE	*437 541*	**32.**	JERNBANEPERSONALETS SPAREBANK	*5 112*
3.	SPAREBANK 1 SR-BANK	*112 010*	**33.**	NØTTERØY SPAREBANK	*5 086*
4.	SPARBANKEN VEST	*81 183*	**34.**	MODUM SPAREBANK	*4 738*
5.	SPAREBANK 1 SMN	*80 965*	**35.**	TIME SPAREBANK	*4 682*
6.	SPAREBANK 1 NORD-NORGE	*61 962*	**36.**	SKUDENES & AAKRA SPAREBANK	*4 278*
7.	SANTANDER CONSUMER BANK	*40 684*	**37.**	MELHUS SPAREBANK	*4 104*
8.	SPAREBANKEN HEDMARK	*38 793*	**38.**	BANK NORWEGIAN	*3 777*
9.	SPAREBANKEN MØRE	*37 165*	**39.**	FLEKKEFJORD SPAREBANK	*3 631*
10.	BNBANK	*34 803*	**40.**	SPAREBANK 1 GUDBRANDSDAL	*3 567*
11.	STOREBRAND BANK	*33 797*	**41.**	RØROS SPAREBANK	*3 279*
12.	SPAREBANKEN SØR	*32 225*	**42.**	LARVIKBANKEN BRUNLANES SPAREBANK	*3 276*
13.	NORDLANDSBANKEN	*29 855*	**43.**	LOM OG SKJÅK SPAREBANK	*3 183*
14.	SPAREBANKEN PLUSS	*29 343*	**44.**	ASKIM SPAREBANK	*3 017*
15.	SANDNES SPAREBANK	*25 595*	**45.**	ODAL SPAREBANK	*2 944*
16.	SPAREBANKEN SOGN OG FJORDANDE	*25 496*	**46.**	BAMBLE OG LANGESUND SPAREBANK	*2 883*
17.	BANK 1 OSLO	*23 382*	**47.**	INDRE SOGN SPAREBANK	*2 878*
18.	SPAREBANKEN ØST	*22 272*	**48.**	SØGNE OG GREIPSTAD SPAREBANK	*2 799*
19.	HELGELAND SPAREBANK	*16 447*	**49.**	EIDSBERG SPAREBANK	*2 752*
20.	GJENSIDIGE BANK	*16 118*	**50.**	KRAGERØ SPAREBANK	*2 711*
21.	FANA SPAREBANK	*11 683*	**51.**	ORKDAL SPAREBANK	*2 690*
22.	TOTENS SPAREBANK	*10 595*	**52.**	MARKER SPAREBANK	*2 686*
23.	SEB PRIVATBANKEN	*9 654*	**53.**	SURNADAL OG STANGVIK SPAREBANK	*2 579*
24.	LANDKREDITT BANK	*8 688*	**54.**	VOSS SPAREBANK	*2 550*
25.	SPAREBANK 1 NORDVEST	*8 274*	**55.**	SELBU SPAREBANK	*2 406*
26.	HAUGESUND SPAREBANK	*6 007*	**56**.	VEKSELBANKEN	*2 347*
27.	AURSKOG SPAREBANK	*5 793*	**57.**	HARSTAD SPAREBANK	*2 228*
28.	SPAREBANK 1 SØRE SUNNMØRE	*5 771*	**58.**	KVINESDAL SPAREBANK	*2 203*
29.	SPARESKILLINGSBANKEN	*5 666*	**59.**	TINN SPAREBANK	*2 154*
30.	KLEPP SPAREBANK	*5 157*	**60.**	LILLESANDS SPAREBANK	*2 073*

61.	LUSTER SPAREBANK	*2 072*	**88.**	BJUGN SPAREBANK	*1 377*
62.	ØRLAND SPAREBANK	*2 042*	**89.**	SPAREBANKEN HEMNE	*1 370*
63.	BUD FRÆNA OG HUSTAD SPAREBANK	*2 035*	**90.**	ETNE SPAREBANK	*1 363*
64.	OPDALS SPAREBANK	*2 016*	**91.**	HEGRA SPAREBANK	*1 315*
65.	HJELMELAND SPAREBANK	*1 982*	**92.**	ÅFJORD SPAREBANK	*1 297*
66.	TOLGA-OS SPAREBANK	*1 981*	**93.**	VERDIBANKEN	*1 225*
67.	ARENDAL OG OMEGNS SPAREBANK	*1 969*	**94.**	EVJE OG HORNNES SPAREBANK	*1 198*
68.	BANK 2	*1 965*	**95.**	VALLE SPAREBANK	*1 095*
69.	STRØMMEN SPAREBANK	*1 945*	**96.**	GJERSTAD SPAREBANK	*1 077*
70.	MELDAL SPAREBANK	*1 944*	**97.**	RINDAL SPAREBANK	*1 073*
71.	BERG SPAREBANK	*1 905*	**98.**	BIRKENES SPAREBANK	*1 041*
72.	BLAKER SPAREBANK	*1 885*	**99.**	SOKNEDAL SPAREBANK	*1 025*
73.	TRØGSTAD SPAREBANK	*1 862*	**100.**	NESSET SPAREBANK	*1 014*
74.	HJARTDAL OG GRANSHERAD SPAREBANK	*1 846*	**101.**	NETFONDS BANK	*933*
75.	GRONG SPAREBANK	*1 815*	**102.**	HALTDALEN SPAREBANK	*917*
76.	STADSBYGD SPAREBANK	*1 789*	**103.**	VIK SPAREBANK	*853*
77.	HØNEFOSS SPAREBANK	*1 777*	**104.**	TYSNES SPAREBANK	*795*
78.	ANDEBU SPAREBANK	*1 730*	**105.**	TYSNES SPAREBANK	*778*
79.	SUNNDAL SPAREBANK	*1 728*	**106.**	AURLAND SPAREBANK	*684*
80.	ØRSKOG SPAREBANK	*1 684*	**107.**	VESTRE SLIDRE SPAREBANK	*577*
81.	KLÆBU SPAREBANK	*1 675*	**108.**	LOFOTEN SPAREBANK	*517*
82.	SPYDEBERG SPAREBANK	*1 669*	**109.**	ETNEDAL SPAREBANK	*477*
83.	FORNEBU SPAREBANK	*1 605*	**110.**	GILDESKÅL SPAREBANK	*459*
84.	YA BANK	*1 572*	**111.**	VANG SPAREBANK	*446*
85.	DRAGNEDAL OG TØRDAL SPAREBANK	*1 471*	**112.**	CULTURA SPAREBANK	*368*
86.	AASEN SPAREBANK	*1 467*			
87.	GRUE SPAREBANK	*1 460*			

Appendix 2: Methodology

A.2.1 Fixed effects estimation

The intuition behind the (one-way) fixed effects estimation method can be illustrated by considering our general model:

(A1) $$ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{5} \beta_n X_{nbt} + \gamma_b + \varepsilon_{bt}$$

Where β_1, β_2, and β_n are coefficients linked to the independent variables of concentration, risk, and controls that are included in the model. The bank-specific fixed effects are represented by the intercept γ_b which has no subscript *t* to illustrate the lack of time dimension. If we were to estimate this model by the use of pooled OLS, our results could suffer from endogeneity problems and thus produce biased results. To see why, we can consider the composite error term of the model $v_{bt} = \gamma_b + \varepsilon_{bt}$. A crucial assumption in OLS is that the error term v_{bt} has to be uncorrelated with the independent variables in order for the model to be unbiased. Although we might assume that the time-varying error ε_{it} is uncorrelated with all of our explanatory variables in all periods (strict exogeneity), the same is not necessarily true for the bank-specific fixed effects γ_b, $Cov(X_{btj,}\, \gamma_b) \neq 0 \; t = 1,2 \ldots, T; j = 1,2 \ldots, k$.

Within group transformation

To cope with the potential endogeneity problem, the fixed effects estimator removes the bank-specific parameter γ_b from the equation by performing a within group (fixed effects) transformation:

(A2) $$\begin{aligned} ROA^*_{bt} &= ROA_{bt} - \overline{ROA_b} \\ &= (\beta_0 - \beta_0) + \beta_1(CM_{bt} - \overline{CM_b}) + \beta_2\left(Risk_{bt} - \overline{Risk_b}\right) + \\ &\sum_{n=3}^{5} \beta_n (X_{bt} - \overline{X_b}) + (\gamma_b - \gamma_b) + (\varepsilon_{bt} - \overline{\varepsilon_b}) \\ &= \beta_1 CM^*_{bt} + \beta_2 Risk^*_{bt} + \sum_{n=3}^{5} \beta_n X^*_{bt} + \varepsilon^*_{bt} \end{aligned}$$

Where $\overline{x_b} = \frac{x_{b,t-1}+x_{b,t-2}+x_{b,t-3}+\cdots+x_{b,t-T}}{T}$ is the within-group average of variable x. Due to the lack of time dimension, γ_b has been removed from the equation. In addition, the within transformation excludes the intercept, which means that the regression line goes through the origin.

Least squares dummy variable approach (LSDV)

Another way of dealing with unobserved fixed effects is to view γ_b as parameter to be estimated by including N-1 dummy variables for each cross-sectional observation. In this way one controls for cross-sectional variation and γ_b is taken out of the error term and included in the model to be quantified. The model can then be estimated by using OLS. LSDV can be illustrated by the model below:

(A3) $ROA_{bt} = \beta_0 + \beta_1 CM_{bt} + \beta_2 Risk_{bt} + \sum_{n=3}^{5} \beta_n X_{nbt} + \gamma_2 D^{i=2} + .. + \gamma_n D^{i=n} + \varepsilon_{bt}$

The dummy variable approach will produce identical results as the within group transformation. However, since we are operating with a relatively large number of banks (N), the LSDV approach would lead to the inclusion of an additional N-1 explanatory variables, which is not practical.

* Note that an independent variable that has little or no variation over time cannot be estimated by the estimation methods mentioned above.

A.2.2 Random effects estimation

Given an assumption of no correlation between the unobserved factors contained in the parameter γ_b and the explanatory variables, our general model turns into a random effects model and can be estimated to produce consistent estimates by using OLS. However, the following estimates would turn out to be inefficient due to the presence of serial correlation in the model's composite error term, $v_{bt} = \gamma_b + \varepsilon_{bt}$. The presence of serial correlation is evident when considering the fact that the time-invariant effect γ_b are contained in the composite error term v_{bt} in each period. To encounter the issue of serial correlation we can perform a GLS-transformation:

(A4) $ROA_{bt} - \theta\overline{ROA_b} = \beta_0(1 - \theta \cdot 1) + \beta_1(CM_{bt} - \theta\overline{CM_b}) + \beta_2\left(Risk_{bt} - \theta\overline{Risk_b}\right) + \sum_{n=3}^{5} \beta_n \left(X_{bt} - \theta\overline{X_b}\right) + v_{bt} - \theta\overline{v_b}$

Where $v_{bt} = \gamma_b + \varepsilon_{bt}$, $\theta = 1 - \left[\frac{1}{1+T\left(\frac{\sigma_\gamma^2}{\sigma_\varepsilon^2}\right)}\right]^{1/2}$ and $0 < \theta < 1$

Instead of subtracting the entire individual time-average from each variable, only a fraction θ is subtracted. Thus, the GLS estimator is a weighted average of *within* and *between* estimators and utilizes the variance within each bank as well as some of the variance between banks. From the expression of θ, we can see that the fraction subtracted are determined by σ_γ^2, σ_ε^2, and the number of time periods. In a case where θ is close to zero, most of the variance in the model is driven by σ_ε^2 and the GLS estimator approaches pooled OLS. If θ is close to one, σ_γ^2 dominates and GLS approaches fixed effects. However, the magnitude of θ is unknown at the outset and has to be estimated in order to be quantified. The value of θ is in practice neither zero nor one but is often closer to one since the model's total variance is often driven by the variance in the unobserved effects σ_γ^2 (Woolridge, 2014).

Appendix 3: An overview of our subsample

The table below presents the subsample of saving banks and their average total assets in the sample period

	Banks	*Size (in mill.)*
1.	SPAREBANK 1 SR-BANK	*112 010*
2.	SPARBANKEN VEST	*81 183*
3.	SPAREBANK 1 SMN	*80 965*
4.	SPAREBANK 1 NORD-NORGE	*61 962*
5.	SPAREBANKEN MØRE	*37 165*
6.	SPAREBANKEN SØR	*32 225*
7.	SPAREBANKEN PLUSS	*29 343*
8.	SANDNES SPAREBANK	*25 595*
9.	SPAREBANKEN SOGN OG FJORDANDE	*25 496*
10.	SPAREBANKEN ØST	*22 272*
11.	HELGELAND SPAREBANK	*16 447*
12.	FANA SPAREBANK	*11 683*

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