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The effect of competition on non-performing loan rates

Evidence from the Norwegian banking market

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Abstract

The relationship between bank competition and financial stability has been thoroughly debated over the last decades. The importance of a stable banking system for financial stability makes this a topic of interest for both economists and regulators. The aim of this thesis has been to investigate how competition in the Norwegian banking market affects the risk-exposure of the loan portfolios. We also relate our findings to earlier contributions on this topic in the theoretical and empirical literature.

Using accounting data for Norwegian banks over the last 20 years, we assess the relationship between the rate of non-performing loans and different measures of competition. Competition measures include concentration indexes, interest rate margin, and the H-statistic.

We find a non-linear relationship between market concentration and loan risk. For low levels of concentration, increased concentration reduces non-performing loan rates. Past a certain level of concentration, this relationship is reversed. Our findings indicate that the Norwegian banking market today is close to this optimal level, suggesting that a continued increasing trend in concentration will contribute to higher non-performing loan rates.

Using the interest rate margin and the H-statistic as competitive measures, we find a linear positive relationship between competition and non-performing loan rates. Provided that these measures capture competitive behavior, this implies that competition increases loan risk.

Our findings are consistent with both the franchise value hypothesis, and the theoretical model proposed by Martinez-Miera and Repullo (2010). The findings are also similar to that of earlier empirical research, and underline how results depend on the choice of competition measure.

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1. Introduction

1.1 Motivation and purpose

Banks serve an important role in the economy. They are intermediaries of transactions, offer credit to borrowers and they accept and manage deposits for the public. Financial crises often spread out to other industries in the economy via the banking system. This can happen due to reduced credit availability, disturbed interbank lending or frozen payments (Berger, Klapper, & Turk-Ariss, 2008). Ensuring a stable banking system is therefore crucial for financial stability. However, financial crises over the last decades have exposed the vulnerability of the banking system to excessive risk taking by individual banks.

For several decades, economic literature has investigated a possible link between the degree of competition in the banking market and the incentives for banks to take risk. The main motivation is that excessive competition between banks has been blamed for past financial crises. However, competition in banking markets is generally thought to be positive for consumers, ensuring greater variety in financial products and wider access to credit. Empirical studies have also found competition in banking markets to be an important factor for economic growth (Bikker, Shaffer, & Spierdijk, 2012).

Allen and Gale (2003) argue that while costs of financial instability are large and apparent, efficiency gains of competition are harder to measure and are born continuously. As a result, the common perception that increased competition may hurt financial stability can lead policymakers to favor concentration over competition in banking markets.

Differing views on the effects of competition in banking markets has created the foundation for an ongoing debate about whether competition contributes positively or negatively to financial stability. The literature has divided itself into two main paradigms: Competition-fragility and competition-stability. The competition-fragility paradigm claims that competition creates incentives for banks to take more risk, while the competition-stability paradigm argues the opposite: competitive behavior secures financial stability. Both views are well founded in microeconomic theories, and could all be valid in different market situations. Recent literature has therefore attempted to reconcile the seemingly conflicting theories. Several empirical studies have also attempted to investigate this relationship, although yielding equally divergent results.

In Norway, banking competition has recently attracted considerable attention in the public debate. The main focus of the debate has been on whether the competitive level is sufficient, or if Norwegian banks are allowed to charge excessive interest rate margins. However, less focus has been directed towards the potential negative consequences of increased competition on financial stability.

This master thesis aims to investigate how risk-taking of Norwegian banks is affected by changes in competition. To analyze this relationship, we focus on the risk-exposure of banks' loan portfolios. We use a panel of quarterly accounting data for all Norwegian banks over the last two decades. Our analysis is similar to comparable studies (Berger, Klapper, & Turk-Ariss, 2008; Jiménez, Lopez, & Saurina, 2013), using a collection of competition measures to explain the riskiness of banks' loan portfolios. To the authors' knowledge, this topic has not previously been studied for the Norwegian banking market.

1.2 Research question

This thesis aims to investigate the following research question:

> *How does the competitiveness of the Norwegian banking market impact the risk exposure of the banks' loan portfolios?*

We attempt to address this question by regressing various competitive measures on the banks' rate of non-performing loans.

1.3 Outline

The rest of this thesis is organized as follows: In **section 2** we review relevant theoretical and empirical literature. This provides a context for understanding how competition may impact banks' risk-taking, and how this has been studied in the past. **Section 3** presents the general econometric model used for our analysis. This general model is later estimated by using different measures of competition. In **section 4** we present our data and explain how variables included in our model are defined and calculated. **Section 5** provides descriptive statistics. This allows us to study important developments in the Norwegian banking market during our sample period. **Section 6** discusses our estimation method, while **section 7** presents the results from the analysis. Finally, **section 8** concludes.

2. Literature review

The relationship between competition and stability in the banking system has been subject to a great amount of research in both theoretical and empirical literature. Since banks are exposed to many sources of risk, the literature offers several points of view on how competition may affect banks' risk exposure. Some of these sources of risk are difficult for the bank to control, such as the risk of a bank run. Other sources of risk are more closely related to risk preference, such as the exposure of the banks' loan portfolios. We concentrate on literature that describe how competition affects the risk-taking decisions of banks. We also describe some of the methods used to investigate the relationship between competition and bank risk in empirical studies. Choosing appropriate measures of risk and competition are especially important decisions in this context.

2.1 Theoretical Literature

There is no clear consensus in the theoretical literature on exactly how competition in the banking markets affect banks' exposure to risk. With respect to the relationship between competition and stability, the theoretical literature is divided between two different paradigms: competition-fragility and competition-stability.

2.1.1 Competition-fragility

The competition-fragility paradigm has a strong standing within banking literature, and has been supported over time both theoretically and empirically. This is the view that competition hurts financial stability by increasing banks' risk exposure.

Keeley (1990) started this strand of literature by introducing the "franchise value" hypothesis. He claimed that the sharp increase in bank failures during the 1980s could be attributed to financial deregulation in the preceding decades. According to Keeley, removal of regulatory barriers intensified the competition between banking organizations, which had a negative effect on the banks' profit margins. This, in turn, decreased the franchise value of the banks, defined as the market value beyond the banks' book values. Keeley found this reduction in franchise value to have caused an increase in banks' risk taking.

Hellmann, Murdoch and Stiglitz (2000) contributed to the franchise value hypothesis by stating that competition in the deposit market increases the moral hazard incentives of banks. According to the authors, the franchise value can only be captured if the bank remains in business and therefore represents the opportunity cost for the bank of going bankrupt. They argue that increased competition for deposits diminishes the profitability of banks and reduces franchise values. As a result, competition gives banks an incentive to increase their risk exposure and gamble with the depositors' money. In another paper, Matutes and Vives (2000) also argue that high levels of competition in the deposit market leads to excessive risk taking by banks.

Increased competition between banks may also have a negative effect on the credit-worthiness of the banks' loan applicants. This is due to an *adverse selection* problem in the loans market (Broecker, 1990; Shaffer, 1990). In a market with many banks, a rejected loan applicant is able to re-apply for a loan at competing banks. If the banks' credit screenings are independent of each other and the judgment errors being made differ across banks, the amount of loan applicants being approved by at least one bank will increase with the number of banks (Broecker, 1990). This implies that the average creditworthiness of the pool of applicants is a decreasing function of the number of banks.

Allen and Gale (2000) discuss the effects of increased competition on the risk of contagion in the financial system. In the case of a small aggregate shock in demand for liquidity, perfect competition in the interbank market can lead to systemic risk. When each bank is small compared to the whole market, it will act as a price taker and have no incentive to provide liquidity to another troubled bank, thereby causing contagion to spread. Under these assumptions, it may therefore be optimal with an imperfectly competitive interbank market.

2.1.2 Competition - stability

The competition-stability paradigm supports the view that less competition leads to a more stable banking system. Fundamental for this view is the article from Stiglitz and Weiss (1981) studying mechanisms in the loan market that result in credit rationing.

In the loan market one would expect that a shortage of available capital would simply raise the lending rate, and the market would return to equilibrium. However, market equilibrium is not necessarily the optimal solution for banks if interest rates are too high. This is caused by the following market mechanisms:

The *adverse selection* aspect is a result of imperfect information in the loan market. A borrowers' probability of repaying their loans varies between individuals, and higher rates attract riskier borrowers; they are willing to borrow at the high rate because the probability of repaying the loan is lower. A higher rate and a subsequent higher margin for the bank is not necessarily profitable since this also attracts more risk.

The *moral hazard* aspect relates to the behavior of the borrowers. When already existing customers face higher interest rates, they will seek more risky projects. This is caused by the payoff profile. If the project goes bankrupt, the lending bank will cover the losses, while an upside for the project will pay out all surpluses to the borrower.

Boyd and De Nicolo (2005) draw on these market mechanisms in their theory about competition and market risk. They criticize the proponents of the franchise value perspective for assuming exogenous distribution of return on the bank's investments. Investments risk and return may in fact be endogenous and depend on the amount of competition in the market. This makes competition an important determinant of risk in both the loan and deposit market.

By assuming that increased competition lowers interest rates, Boyd and De Nicolo (BDN) establish a relationship between competition and risk called the *risk shifting*-effect. This is the argument that while higher interest rates increase the franchise value of the banks, the franchise values of the borrowers' projects decrease. Low levels of banking competition therefore increase the riskiness of the borrowers. They argue that this is in essence a principal-agent relationship that exists in both the loan and deposit market. In the deposit market, the bank will be the one taking less risk with depositors' money if the deposit interest rates are low. When margins are higher, banks take less risk. Evidently, competition in the deposit and loan markets has opposite effects on bank risk. The authors conclude that a bank's risk profile will be unaffected by changes in competition when the banks compete in both markets.

The “too big to fail”-hypothesis (Mishkin, 1999) is another argument that competition may have positive effects on financial stability. Due to implicit guarantees by the government, banks above a certain size believe that they will always be saved through public bailouts. This is because the social cost of failure succeeds the private cost when the banks are large enough to have systemic importance. This stimulates these banks will be more risk seeking, knowing that negative consequences will be covered by the government. In a more fragmented banking market, the problem of excessive risk taking due to banks being “too big to fail” will be reduced.

2.1.3 Reconciling literature

The competition-stability view promotes competition between banks in order to achieve a stable banking system. The competition-fragility view promotes the opposite. While these theoretical views seem to contradict, the two paradigms are not necessarily mutually exclusive. Considering the many mechanisms at work, the relationship between competition and stability could be more complex than a simple positive or negative trade-off.

Berger, Klapper and Turk-Ariss (2008) point out that the lack of consensus in the literature may be explained by the need to distinguish between loan portfolio risk and overall bank risk. The competition-fragility view tends to focus on the positive effects of market power on the incentives for banks to reduce their overall risk of bankruptcy. On the other hand, literature within the competition-stability view puts emphasis on the negative effects of market power on loan portfolio risk. Even if market power in the loan market does in fact increase loan portfolio risk, higher interest rates should also contribute to increased franchise values. In order to protect their gain in franchise value, banks may offset the higher loan risk by mitigating other sources of risk, thereby reducing overall bank risk (Berger, Klapper, & Turk-Ariss, 2008).

Martinez-Miera & Repullo (MMR, 2010) build on the model by Boyd and De Nicolò (2005). They also analyze risk of failure for banks investing in entrepreneurial loans when the probability of the loans defaulting is endogenous and depends on the competition. The important extension in the MMR-model is that it allows for imperfectly correlated loan defaults, meaning that loans do not necessarily default at the same time. The risk of bank default does not necessarily increase with higher interest rates, because performing loans still make payments, now with an even higher margin. This *margin effect* opposes the *risk-shifting* effect from the BDN-model by increasing the buffer to cover loan losses when interest rates rises. The net effect of interest rate changes on risk is ambiguous. MMR go on to evaluate these effects at different levels of competition, finding a nonlinear U-shaped relationship, reconciling simple linear effects as suggested by previous theories. They find that the margin effect almost always dominates the risk-shifting effect, making increased competition lead to higher risk of bank failure. The exception is in very collusive markets, where the risk-shifting effect dominates; increased competition decreases risk of bank failure.

These explanations suggest that all theories could represent valid mechanisms responding to banking competition. Which mechanisms are dominant and which measures of competition and risk that best captures this relationship, is an issue relevant for empirical analysis.

2.2 Empirical literature

Several empirical studies have investigated the relationship between the competitive level in banking markets and banks' risk taking. As in the theoretical literature, the empirical literature is inconclusive and the results vary with the different measures of competition and risk. The sample and time period analyzed is also an important determinant of the empirical findings (Carletti, 2010).

2.2.1 Empirical strategies in the literature

A distinction between the different empirical studies is the measures used to explain competition. In economic theory, competition determines the firms' ability to charge a mark-up over the cost price of their output. A measure of the price-cost margin would therefore indicate competitiveness. The Lerner index, which equals the difference between the market price and marginal cost divided by the output price, is closely related. The challenge with this measure is that it requires access to detailed data on banks' prices and marginal cost. Since this information is not easily accessible, competition is commonly estimated using other proxies (Bikker & Spierdijk, 2010).

One such set of proxies is measures of market concentration. Examples are the Herfindahl-Hirschman index (HHI), the number of banks, and measures of the market share of the five largest banks (C5). The theoretical basis for using such indexes to measure competition is the structure-conduct-performance (SCP) hypothesis. This states that market concentration creates an environment with collusion and less competitive behavior. According to this hypothesis, concentration is therefore a suitable inverse measure of competition.

Theoretical literature on banking competition and risk generally do not distinguish between competition and concentration (Carletti, 2010). However, the assumption that concentration is a measure that can capture competitiveness is debated in empirical literature. One counter-argument to the SCP hypothesis is that market concentration may be a natural consequence of efficient firms gaining market shares. This view is proposed by the efficient structure (ES) hypothesis, which states that concentration is endogenous and does not necessarily impair competition. Various empirical studies find results both in favor of both the SCP and ES. In a survey of this literature, Berger, Demirgüç-Kunt, Levine and Haubrich (2004) conclude that concentration measures are not reliable as sole indicators of market competition.

Several other estimation methods have emerged in response to the need for other measures that can describe competitive behavior. The new empirical industrial organization approach (NEIO) bases competitive measures on microeconomic models, and is more closely related to the price-cost margin. Examples of such measures are proposed by Panzar-Rosse (1987), Bresnahan (1982) and Boone et al. (2007) (Bikker & Spierdijk, 2010).

The most widely applied approach to estimate competition in the banking sector is the Panzar and Rosse method (P-R). This method measures market power as the extent to which a change in a firm's factor input prices will be reflected in the equilibrium revenues earned by the firm (Bikker & Haaf, 2002). The resulting measure is the H-statistic, which is the sum of elasticities of revenue with respect to factor prices. The H-statistic has a range of $[-\infty, 1]$, where a value of 1 will indicate perfect competition, positive values less than one are consistent with monopolistic competition and negative value are in line with collusive or monopolistic behavior. According to Carletti (2010), the P-R approach has a solid theoretical foundation. However, it makes the assumption that the industry is in long-term equilibrium, which in reality is rarely the case.

In terms of measuring stability, variables may either capture individual bank risk or systemic risk. One of the most commonly used measures of individual bank risk is the ratio of non-performing loans to total loans ($NPLrate$). It measures the risk of the loan portfolio of the bank. Another individual bank risk parameter is the *Z-score,* which describes a bank's proximity to bankruptcy. It equals the number of return on assets (ROA) standard deviations that ROA must decrease with for the bank to be insolvent. Measures of systemic risk include the degree of correlation between banks' stock returns (Carletti, 2010).

2.2.2 Empirical findings on banking competition and stability

Empirical studies investigating the relationship between competition and stability are performed either for individual countries or over cross-country samples.

In a study of the Spanish banking market, Jiménez, Lopez and Saurina (2013) investigate Martinez-Miera and Repullo's theory of a non-linear relationship between banking competition in the loans and deposit markets and risk-taking. Using $NPLrate$ as the dependent risk variable, the authors find support of a non-linear relationship when using market concentration indexes in the loans market as competition measures. However, when using Lerner indexes the results for the loans market are more in support of the original franchise value hypothesis.

Cross country-studies have been performed over the last years due to the new availability of comparable data across countries. In a summary of the literature on banking competition and stability, Carletti (2010) points out that cross-country studies generally find a positive relationship between competition and stability in the banking sector. These same cross-country studies also find a positive correlation between concentration and stability. This could imply that the benefits from concentration in terms of stability are not a result of lower competition, but through other effects such as diversification.

In a comprehensive cross-country study using data for 8235 banks in 23 developed nations, Berger, Klapper and Turk-Ariss (2008) test how the empirical relationship between risk and competition is affected by using different measures of banking risk and market power. Their findings indicate that while banks enjoying higher market power have less overall risk exposure (measured by $Z\text{–}score$), they also have higher loan portfolio risk (measured by $NPLrate$). The results thus provide support of both the competition-fragility and competition-stability views.

Tabak, Fazio and Cajueiro (2012) perform a cross-country study investigating the relationship between competition and financial stability for 10 Latin American countries in the period 2003-2008. They find a significant non-linear relationship, but unlike other studies the estimated coefficients indicate that both high and low competition increase financial stability. Rather than explaining individual bank risk measures, this study use a measure of stability derived from estimation of a stability stochastic frontier.

2.2.3 Competitive studies of the Norwegian banking market

While we have not found studies that investigate the competition-risk relationship specifically for the Norwegian banking market, Norway is included in the sample for the cross-country study of Berger, Klapper, & Turk-Ariss (2008). In the spring of 2015, the Norwegian Competitive Authority (NCA) released a report analyzing the competitive environment in the Norwegian home mortgage market. The report was initiated on the basis of growing concern that Norwegian banks are using their market power to coordinate interest rate levels. NCA gathered detailed data from eleven banks in Norway, and focused on the banks' interest rate margins as an indicator of competitive behavior. Although the report does not reflect on the link between competition and the banks' risk exposure, it concludes that the Norwegian mortgage market suffers from insufficient competition (NCA, 2015).

3. Econometric model

In order to investigate the relationship between competition and risk in the banking market, we choose to estimate the following general model:

(1) $NPLrate_{i,t} =$
$\beta_0 + \sum_{j=1}^{4} \beta_j \left(NPLrate_{i,t-j}\right) + \beta_5 Competition_{i,t} + \beta_6 Competition_{i,t}^2 +$
$\sum_{n=1}^{M} \kappa_n (Control\ variable_{i,t,n}) + \varepsilon_{i,t}$

We use the ratio of non-performing loans to total loans ($NPLrate_{i,t}$) as the dependent variable, measuring the risk exposure of banks' loan portfolio. This allows us to explain banks' risk-taking behavior in the loan market.

Our model includes four lagged terms of the dependent variable, to account for the persistence in non-performing loan rates. This has consequences for our choice of estimator, which will be discussed in section 6.

We will attempt to estimate our model by including different measures of competition. The competition measures are chosen on the basis of being both commonly applied in empirical literature, and within the limits of our available data. These include concentration measures, interest rate margin, and the H-statistic. In section 4, we explain in greater detail how these variables are constructed.

Recent literature has argued that competition may affect the risk-taking of banks through many different channels (Boyd & De Nicolò, 2005; Berger, Klapper, & Turk-Ariss, 2008; Martinez-Miera & Repullo, 2010). As a result, the relationship between competition and risk may be non-linear. We investigate this by including a squared term of the competition measure.

Control variables included both macro trends and bank-specific variables, which may affect the ratio of non-performing loans. M denotes the number of included control variables. Finally, $\varepsilon_{i,t}$ is the model error term.

4. Data and construction of variables

For the analysis in this thesis, we obtain quarterly data on earnings, costs and balance statements of banks operating in Norway starting from the last quarter of 1991, until the end of 2014. The data is assembled by Statistics Norway through financial statements and contained in a database called ORBOF[1], to which all banking corporations operating in Norway are required to report on a quarterly basis.

To allow for risk analysis we have been provided data non-performing loans, a measure consisting of loans for which interest and principal payments have not been paid on time.

All banks operating in Norway are obligated to report financial statements to ORBOF. The banks can be classified as either Norwegian-owned, subsidiaries of foreign banks, as well as branches of foreign-owned banks. Some exceptions apply to Norwegian-registered branches of foreign banks (NUF), which for example are not required to report data on equity ratios.

Banks with activity outside of Norway are required to report for their legal entity, which includes its foreign activities. This concerns DNB, Santander, Nordea and Eika Kredittbank. These banks therefore report for two separate entities in each period. In our empirical analysis, we make sure to only include one of these entities.

The data is reported on a non-consolidated level for the parent bank, excluding activity in subsidiaries. An important issue regarding non-consolidated data is that over the last years, banks have increasingly transferred issued loans to credit institutions. This is a result of new regulation in 2007, which allowed for creation of covered bonds (OMF – obligasjoner med fortrinnsrett). The condition was that the bonds should be issued in separate credit institutions. Since covered bonds are an affordable form of financing for banks, it has become an increasingly important source

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[1] See http://www.ssb.no/innrapportering/naeringsliv/orbof (in Norwegian)

of funding (Bakke & Rakkestad, 2010).

We also collect macroeconomic data on quarterly GDP growth for our whole sample period. The series is calculated from value-change in GDP for mainland Norway. The data is provided and seasonally adjusted by SSB. (Statistics Norway (SSB), 2015)

Data on NIBOR 3-month lending rates is provided by Oslo Stock Exchange through Macrobond. The series is calculated as quarterly averages of daily trading rates on interbank lending for our whole sample period.

4.1 Treatment of the data set

Although the data set spans from 1991Q4, we choose to start our analysis in 1992 because of the banking crisis that occurred in Norway in the period 1988 to 1992. During this crisis, several of the largest Norwegian commercial banks were nationalized to avoid default (Gram, 2011).

For analytical purposes, we omit banks that have less than or equal to 8 consecutive observations (two years or less) of the dependent variable $NPLrate$ in our regressions. This reduces the dataset by 52 non-missing observations. Banks with a shorter life span than this add little explanatory power because of the lag structure in our econometric models. This leaves the dataset with 15732 observations spanning 92 quarters from 1992Q1 to 2014Q4. The number of panels (banks) varies from 156 to 136 in the sample period.

There are certain data points that produce large outliers in our variables. Close analysis show that these outliers are associated with bankruptcies or startups, yielding either very large or very small values. We omit outliers that are 3 standard deviations above or below the median value for variables that are prone to calculation of extreme values[2].

[2] Affected variables are $IRmargin$, ROA and $Equityratio$.

4.2 Variables construction

Using the available data, we construct variables in order to estimate the general model specified in equation (1). How we define and construct the dependent variable, as well as the competition and control variables, is explained below.

4.2.1 Non-performing loan rates

Non-performing loan rates is calculated as the ratio of non-performing loans to total loans for each bank:

$$NPLrate_{i,t} = \frac{Non\text{–}perfoming\ loans_{i,t}}{Total\ loans_{i,t}} * 100$$

A loan is considered non-performing when interest and principal payments have not been paid on time. At that time, the bank is required to estimate the expected loss on the loan (Berge & Boye, 2007).

Since 2007, non-performing loans are reported for the banks' legal entity. This means that for banks with foreign activity (DNB, Nordea, Santander and Eika Kredittbank), reported numbers of non-performing loans include loans made by the bank abroad. The result is that for these banks, the calculated $NPLrate$ after 2007 reflect the rate of non-performing loans for *all* loans, not only domestic. However, the size of the loans made abroad only represents a small fraction of the loan portfolio. We therefore make the assumption that the $NPLrate$ calculated for legal entity can be used as a proxy for the domestic $NPLrate$ for these four banks.

4.2.2 Concentration indexes

We start by creating variables that measure the concentration in the banking market in each time period:

C5-index: A measure representing the sum of the combined market shares of the five largest banks in loans market.

$$C5_t = \frac{\sum_{i=N-4}^{N} Total\ loans_{i,t}}{\sum_{i=1}^{N} Total\ loans_{i,t}} * 100$$

Where N is the total number of banks, sorted by the size of $Total\ loans$.

Herfindahl-Hirschman index (HHI) is calculated as the sum of squared market shares:

$$HHI_t = \sum_{i=1}^{N} Marketshare_{i,t}^{2}$$

HHI has a range of $\frac{1}{N}$ – all have equal market shares, to 1 – one bank has the entire market. It is the most commonly used measure of market concentration. While the C5 index ignores the market share distribution of banks that are not among the five largest banks, HHI includes the market shares of all banks and assigns greater weight to larger banks.

As noted in the previous section, significant amounts of loans have been transferred from parent banks to subsidiary credit institutions since 2007. This affects our calculation of market shares for the banks. Based on comparisons of our estimates with reported consolidated market shares[3], our calculated market shares for the five largest banks range between 0.5-4 percent above consolidated numbers.

4.2.3 Interest rate margin

The level of competition in any market will have an effect on the firms' profit margins. In the case of banks, interest incomes from loans represent a significant part of their earnings base. The interest rate margin for each bank should therefore provide information about the bank's degree of market power or the amount of competition this bank is subject to. This is in line with the view of the Norwegian Competition Authority. In a recent study, they argue that competition in the Norwegian mortgage market is insufficient on the basis of increasing interest rate margins (NCA, 2015).

Since our dataset contains accounts for each bank's total loans issued to customers and quarterly interest income, we are able to construct an implicit measure of the

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[3] See https://www.fno.no/statistikk/bank/ for calculated consolidated market shares for the 10 largest banks in Norway

average interest rate charged on loans. The difference between this interest rate and the banks' funding cost is a measure of the interest rate margin.

When issuing a new loan to households and businesses, the marginal funding source will typically be bonds (Raknerud, Vatne, & Rakkestad, 2011). The interest rate on bonds can be divided into the money market rate (NIBOR) and a risk premium. The risk premiums will depend on both general market conditions and the perceived riskiness of the particular bank (Hoff, 2011), but are difficult to obtain for each bank.

We construct a measure of the interest rate margin for loans applying the 3-month NIBOR (Norwegian Inter Bank Offer Rate) as a proxy for marginal funding cost:

$$IRmargin_{i,t} = \left(\frac{Interest\ income_{i,t}}{Gross\ total\ loans_{i,t}} - NIBOR_t \right) * 100$$

A weakness of this measure is that it does not take into account the issuer-specific risk premium over NIBOR. The advantage is that NIBOR is a measure that reflects market conditions and is the main component of the banks' marginal funding cost (NCA, 2015). $IRmargin$ is denoted in yearly percentages, in order to give intuitive interpretation in the analysis.

4.2.4 The H-statistic

As discussed in the section 2, the Panzar-Rosse (P-R) approach is a widespread method used in empirical studies of competition in the banking market. For a thorough review of different empirical specifications and the underlying assumptions of the model, see for example Bikker, Shaffer and Spierdijk (2012).

In order to estimate the H-statistic for our data, we employ an empirical setup following Bikker and Haaf (2002). The general reduced form equation is:

(2) $$lnII = \alpha + \lambda lnAFR + \gamma lnPPE + \delta lnPCE + \sum_j \xi_j \, lnBSF_j + \eta lnOI + error$$

Where II denotes total interest income, AFR is the annual funding rate, PPE is the price of personnel expenses and PCE is the price of capital expenditure. BSF controls for bank-specific control factors, and OI is the ratio of other income to total assets.

The H-statistic is calculated as the sum of elasticities of interest income with respect to the included input prices.

The sum of these elasticities can be used as a measure of the competitive environment in the market, since it should represent the firm's ability to pass through changes in factor prices to its market. $H = 1$ indicates perfect competition, since a change in factor prices should raise the equilibrium price by the same percentage. $0 < H < 1$ characterizes monopolistic competition, since the firm is able to pass through some of the cost increases by reducing its quantity to raise the price. $H < 0$ indicates behavior in line with monopoly (Bikker & Spierdijk, 2008).

Applying this setup to our data we end up with the following empirical reduced form equation:

(3) $$lnII_{i,t} = \alpha + \lambda\, ln\left(pfund_{i,t}\right) + \gamma\, ln\left(ppers_{i,t}\right) + \delta\, ln\left(pphys_{i,t}\right) + \xi_1 ln\,(loanratio_{i,t}) + \xi_2 ln\,(nonearn_{i,t}) + \xi_3 ln\,(depfund_{i,t}) + \xi_4 ln\,(eqratio_{i,t}) + \xi_5 Fown_{i,t} + \xi_6 Fbank_{i,t} + \eta ln\,(otherinc_{i,t}) + u_{i,t}$$

Where $II_{i,t}$ is total interest income for bank i in period t. Most factor prices are directly unobservable. Following Bikker and Spierdijk (2008), we therefore use interest expenses over total funding ($pfund_{i,t}$) to proxy for average funding rate, personnel expenses over total assets ($ppers_{i,t}$) to proxy for price of personnel expenses and total operating costs over fixed total assets ($pphys_{i,t}$) for the price of capital expenditure.

The following variables control for bank-specific factors: the ratio of total loans to total assets ($loanratio_{i,t}$) controls for differences in credit risk. The ratio of non-earning assets to total assets ($nonearn_{i,t}$) controls for efficiency. We include the ratio of deposits to short term funding ratio ($depfund_{i,t}$) and equity ratio ($eqratio_{i,t}$) to control for funding composition. The ratio of non-interest income over interest income ($otherinc_{i,t}$) controls for the degree of non-financial activities. Finally, we include dummies for subsidiaries of foreign banks ($Fown_{i,t}$) and foreign banks with a branch operating in Norway ($Fbank_{i,t}$) to control for structural differences. In our setup the H-statistic becomes:

$$H\text{–}statistic = \lambda + \gamma + \delta$$

Most commonly, the P-R approach in empirical studies assumes constant competition for the entire sample period resulting in a single H-statistic for each market. However, we are interested in studying how this measure can inform us on how competition in one market has changed over time.

Bikker and Spierdijk (2008) suggest several ways to estimate the H-statistic in order to study the development in competition over time:

- Calculate static estimates of the H-statistic for each period. According to the authors, this approach has the disadvantage of potentially yielding erratic patterns in the H-statistic over time.
- Repeatedly estimate the P-R equation using recursive least squares. This implies starting with a small sub-sample of the dataset and then expanding the sample period with one period at a time. This method allows for gradual change in the competitive environment, and results in quarterly estimates of the H-statistic for the Norwegian banking market.

We also consider an approach where we calculate rolling window estimates. This approach provides us with the reliability of a static H-statistic calculation, but gives us enough variation to see changes in competition over time. In **Appendix 1**, we provide a plot illustrating the estimates of the H-statistic using the different methods. All estimates are obtained using pooled OLS with robust standard errors. Other estimators are also considered. In our analysis we use the H-statistic measure obtained through rolling window estimation.

After years of empirical application, the H-statistic has shown to be quite unreliable. In a recent paper by Spierdijk and Shaffer (2015) summarize the results of empirical papers employing the measure. The H-statistic is thoroughly examined using several standard theoretical models. The authors argue that the H-statistic does not take into account important market aspects such as cost differences, product differentiation, strategic decision variable, action sequencing or collusive behavior. They demonstrate that the measure could take on any value for any degree of competition when these important aspects are neglected, and that the H-statistic should not be considered a reliable measure of competition.

Since the measure is common in banking literature we choose to include it in our analysis, but use caution when interpreting the associated results.

4.2.5 Control variables

We include the following variables controlling for bank-specific effects and macro trends, which may affect non-performing loan rates:

Quarterly GDP growth ($GDPgrowth$) controls for the impact of business cycles on banks' non-performing loan rates. We include four lags of this variable, considering that effects from the business cycle often takes time to develop into non-performing loans on the banks' balance sheets. Non-performing loan rates are likely to increase in bad times and decrease in times of economic growth. We therefore expect a negative effect of GDP growth on non-performing loan rates. The variable $GDPgrowth$ is expressed in yearly growth-percentages.

Return on Assets (ROA) measures the profitability of the bank. Our expectation for the estimated coefficient on this control variable is ambiguous. On the one hand, it is likely that a positive relationship exists between risk and return in the long run. However, high loan losses in particular years might cause a significant reduction in earnings, in which case the variable could have a negative effect on non-performing loans (Jiménez, Lopez, & Saurina, 2013).

Market share ($Marketshare$) is the bank's market share in the loans market. While larger banks have benefits of scale such as risk-diversification, bank managers could also have the incentive to take advantage of this in order to push further along the risk profile of the bank. We therefore have no clear expectation of the sign on this variable's estimated coefficient.

Equity ratio (*Equityratio*) is calculated as equity over total assets. Although there are strict requirements to banks' equity ratios, the funding structure of the banks varies substantially. A higher equity ratio could indicate a lower risk preference of the bank, which should imply less risk. We therefore expect a negative relationship between *Equityratio* and non-performing loan rates.

Lagged dependent variable: We include four lags of the dependent variable to take account for the persistency of the *NPLrate* variable. Non-performing loans may remain on banks' balance sheets for several quarters. Four quarters of lagged values captures this persistence. We expect positive coefficients on the lagged dependent variables.

5. Descriptive statistics

Table 1 provides summary statistics of the variables included in our econometric model. In this section, we attempt to study these variables closer and provide explanations for developments and trends.

Table 1: Summary statistics for regression variables

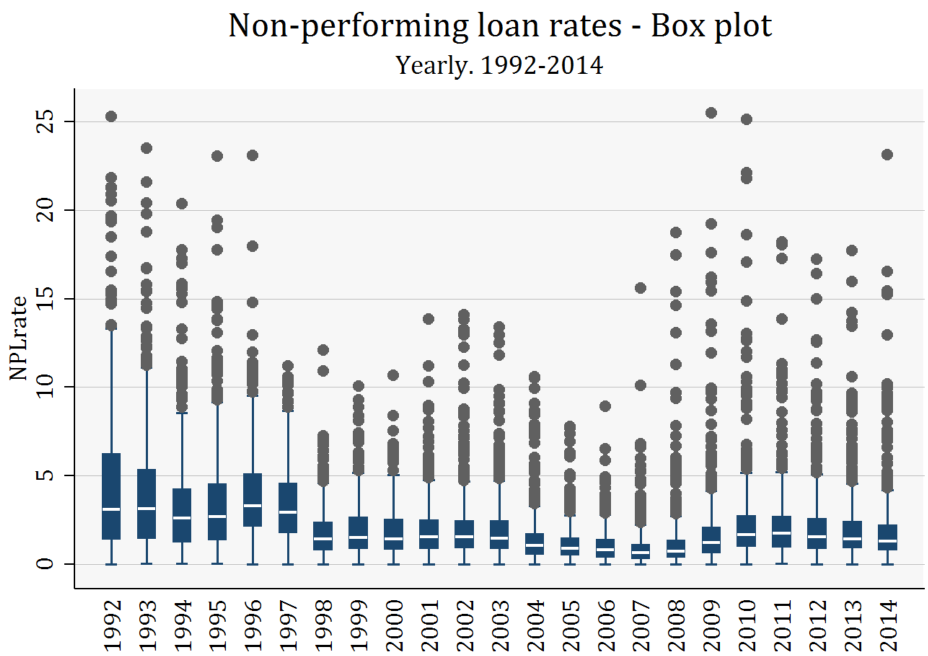
	Mean	Observations	Median	Min	Max	St. dev
NPLrate	2.125	11948	1.47	0.00027	25.1	2.183
C5	59.55	11948	60.06	54.5	64.3	2.498
HHI	0.115	11948	0.11	0.082	0.17	0.025
GDPgrowth	0.731	11948	0.61	-2.28	4.23	0.997
Marketshare	0.692	11948	0.09	0.0022	36.4	2.685
ROA	0.306	11948	0.30	-1.95	2.10	0.263
Equityratio	10.33	11948	9.81	-45.4	50.8	3.910
NIBOR	4.338	11941	3.97	1.48	8.22	2.013
IRmargin	2.781	11941	2.57	-10.4	25.2	1.900
H-statistic	0.270	11279	0.21	-1.23	1.79	0.653

The statistics are based on observations in the sample from regressions in **Table 2** and **Table 3**, with the exception of NIBOR and IRmargin which are based on the corresponding sample from regressions in **Table 4**, and H-statistic which is based on the corresponding sample from regressions in **Table 5**. For summary statistics from the full sample for all variables, see Appendix 2.

5.1 Non-performing loan rates

Non-performing loans is a source of risk for each individual bank. As seen in the summary statistics table, $NPLrate$ varies from rates close to zero to more than 25 percent. To further investigate the spread in non-performing loans over the sample period, we plot all observed values of $NPLrate$. **Figure 1** shows a box plot of the quarterly non-performing loan rates, sorted by year. The blue boxes in the figure plot the interval from the 25th to 75th percentile, while the white line inside the box marks the median. The grey dots indicate observations that lay above the upper adjacent value, defined as $U = x_{75} + \frac{3}{2}(x_{75} - x_{25})$, where x_{75} (x_{25}) represents the value at the 75th (25th) percentile (Tukey, 1977).

Figure 1

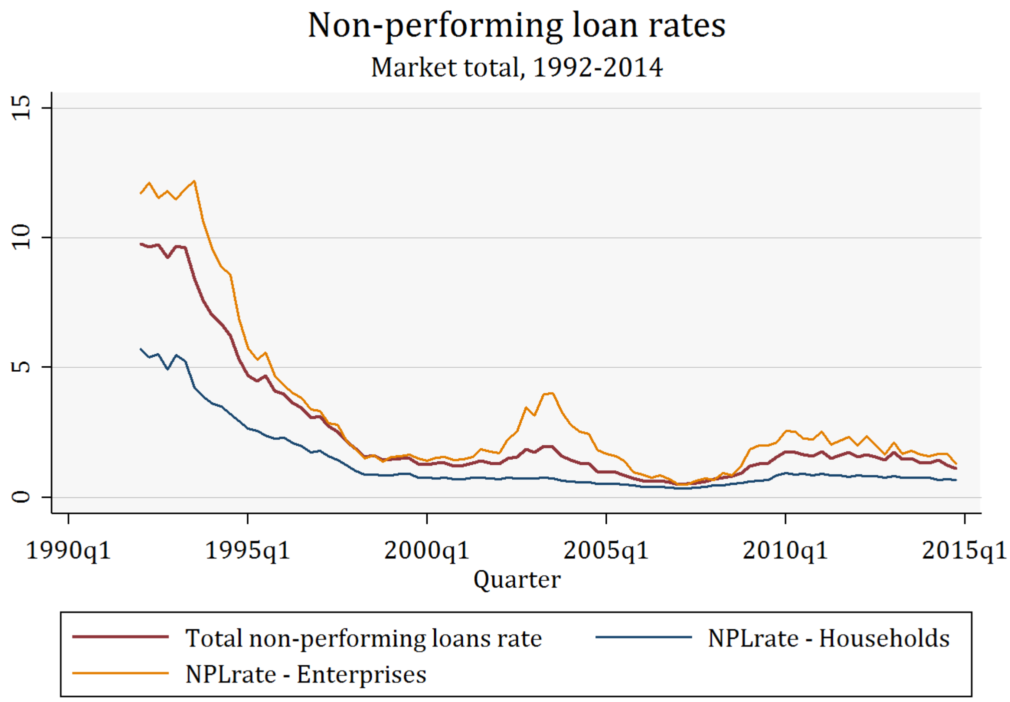


Note: The figure is based on the full sample of the variable as provided in Appendix 2.

The box plot shows that there are several observations within each year that lie outside the upper adjacent value. Closer study reveals that many of these observations are related to banks' starting period, as well as prior to bank closure. A large portion can also be accredited to a small group of banks. This could be due to the fact that some banks specialize within risky segments of the loan market, and therefore consistently operate with high levels of non-performing loans.

The box plot also shows that both the median level and the variation in non-performing loan rates has declined since the beginning of the 1990's. **Figure 2** shows the aggregate non-performing loans rate for the entire market, decomposed into enterprises and households.

Figure 2



Note: The figure is based on the full sample of the variable as provided in Appendix 2.

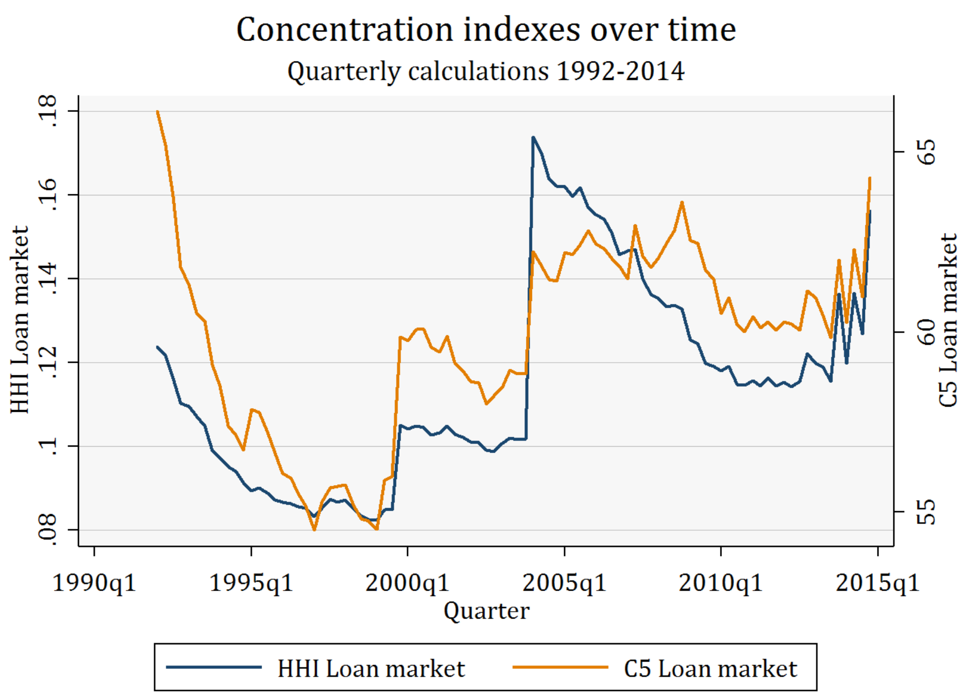
The figures illustrate that after the banking crisis in the 1990s, the total non-performing loans rate has remained stable and low, varying between 1-2%. According to Norges Bank, the rate of non-performing loans in the economy was at a historic low before the financial crisis in 2008. This development has mainly been due to strong economic performance of the economy over the last two decades, as well as high debt growth in both the household and enterprise sectors (Berge & Boye, 2007).

The non-performing portion of loans in the economy is determined by the ability of households and firms to repay their debts. This makes the non-performing loan rates a risk indicator for the economy. The need to control for macroeconomic conditions is confirmed from the figure. It also illustrates that non-performing loans from enterprises are more sensitive to variations in the business cycle. This is because households' incentives to avoid bankruptcy is stronger compared to that of enterprises (Norges Bank, 2014, p. 35).

5.2 Market structure

Two of the measures we use to proxy for competition are concentration indexes, calculated on the basis of market shares for individual banks. To get a clear picture of how market concentration has developed over the sample period, we provide a graph of $C5$ and HHI indexes for the loans market in **Figure 3.**

Figure 3



Note: The figure is based on the full sample of the variable as provided in Appendix 2.

The combined market shares of the 5 largest banks ($C5$) range between 55 and 65 percent over the sample period. Both measures show that concentration has increased since the beginning of the last decade.

Several major developments in the banking market have occurred over the last decades, which have influenced the level of concentration. From 1992 to the end of 2014, there has been a general decrease in the number of banks operating in Norway. The number of savings banks has been the main driver of this decrease, starting at 140 savings banks in 1992 to 107 banks in 2014 (Sparebankforeningen). The total number of banks has decreased from 156 to 136 over the same period.

In 1994 the EEA agreement opened up the Norwegian market for foreign banks. Today, banks with foreign ownership are among the largest in the Norwegian market, including Handelsbanken (branch of foreign bank), Danske Bank (branch of foreign bank), and Nordea (subsidiary). This shows that foreign banks are able to compete with domestic banks in the Norwegian market.

An event that made a large impact on market concentration was the 2003 merger between DnB and Gjensidige NOR, which at the time were the two largest banks operating in Norway. The market share of total loans for the new bank, DNB Bank ASA, was 38 percent after the merger. The event is visible from the spike in HHI. This measure puts greater emphasis on larger banks, since it is calculated as the sum of squared market shares. The increase is not as visible from the plot of the C5-index, since the merger only increased this measure by the market share of the 6th largest bank moving up to 5th place.

The market share of each bank is also included as a control variable in our econometric model. Summary statistics for this variable show that the maximum value of market shares is more than 13 standard deviations away from the mean. The reason is that the Norwegian banking market consists of a few national branch-networks, as well as a large group of small banks only operating in regional and local markets. To illustrate, the combined market share in the gross loans market of the 100 smallest banks was only 8.4 %, compared to a 64,5% market share of the 5 largest banks, at the end of 2014.

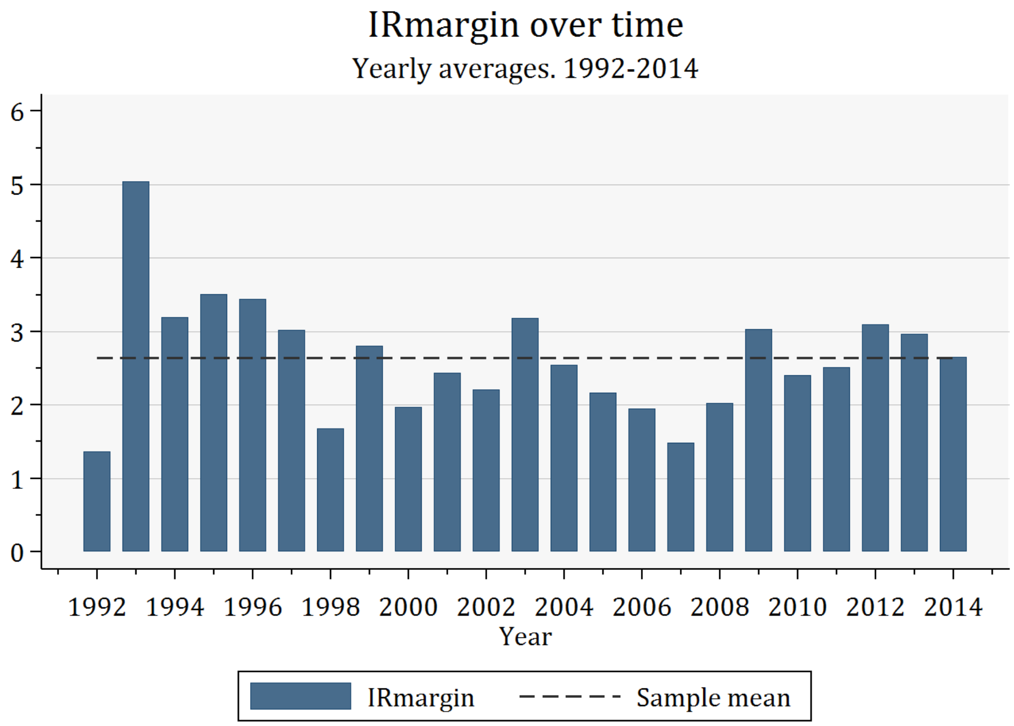
5.3 Interest rate margins and profitability

The interest rate margin variable may capture competitive behavior by measuring the margin that a bank is able to charge on its loans above the funding cost. The summary statistics of the $IRmargin$ reveals that the variable is subject to considerable variation, even after being trimmed for outliers.

Figure 4 plots the yearly averages of $IRmargin$, for the entire market. Even though this graph aggregates the interest rate margin over all banks and within each year, it illustrates that the measure is sensitive to market fluctuations. In their 2015 study, the

NCA argued that the average interest rate margin has been increasing in recent years. They use a sample period from 2007-2015 to make this point. This trend is also evident in our graph. However, when viewed in a larger historical context, interest rate margins for recent years lie close to the average margin for the whole sample.

Figure 4

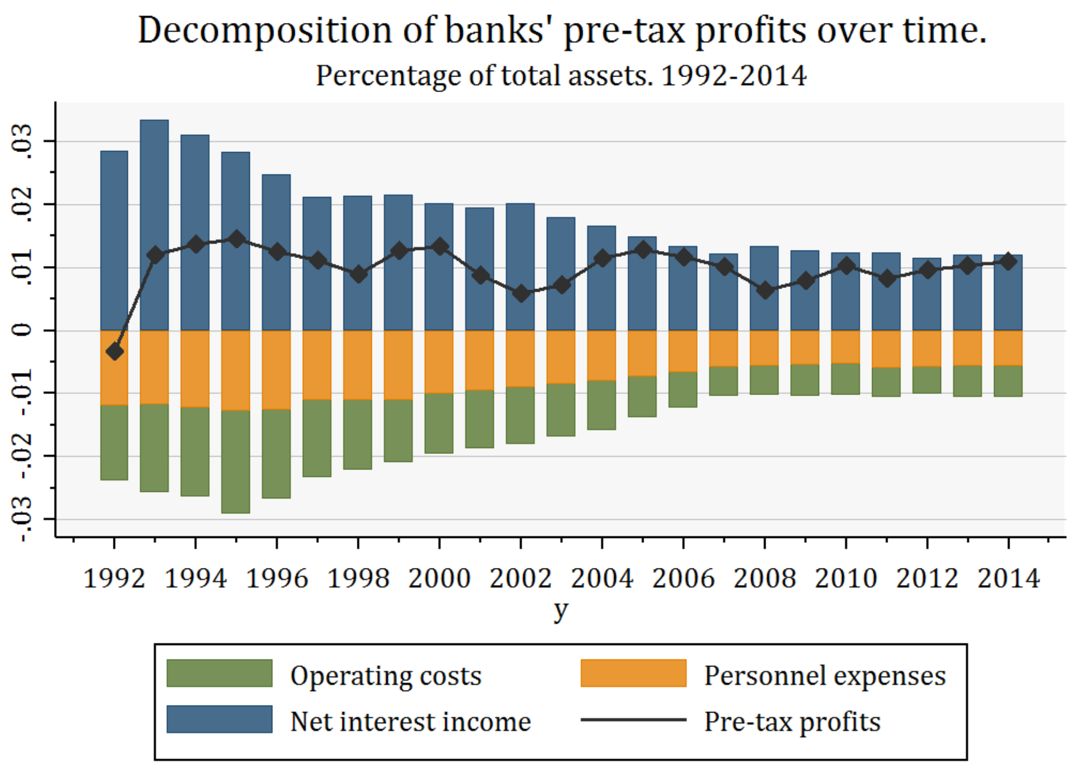


Note: The figure is based on the full sample of the variable as provided in Appendix 2.

An interesting question is whether or not the increasing interest rate margins allows for greater profits, or if it is a result of increasing costs in the banking industry. This has been a subject of particular interest in the debate in Norway since the introduction of new capital requirements.

In **Figure 5**, we decompose banks' profits from 1992 to 2014 into net interest income, personnel expenses and operating costs. Net interest income is defined as $NI = (Interest\ income - Interest\ expenses)$. All variables are calculated as percentages of total assets and weighted according to the bank's relative size of assets.

Figure 5



Note: The figure is based on the full sample of the variables as provided in Appendix 2.

Figure 5 shows that pre-tax profits in the Norwegian banking sector have on average been 1% of total assets the last 20 years. Profitability has varied with the business cycle and has, with the exception of 1992, remained between 0,5% and 1,5%. Although net interest income has been decreasing over the entire time span, profitability has been maintained. An explanation may be the corresponding decrease in both operating costs and personnel expenses, both significant cost figures. This indicates that Norwegian banks have become increasingly efficient over the last two decades.

6. Estimation methods

6.1 Choice of estimator

6.1.1 Fixed effects estimator

Since we are using panel data, the error term in our equation contains both a firm-specific effect that remains constant over time as well as a time- and firm varying component: $\varepsilon_{i,t} = a_i + u_{i,t}$.

One can think of several factors unique for each bank that stay constant over time, that also have an effect on the non-performing loans ratio: management style, banking specialization and ownership structure. Some of these factors will be difficult to control for with explicit variables and will evidently be a part of the error term. These omitted factors are called fixed effects.

An issue when estimating our model is that these fixed effects are a potential source of endogeneity. Bank-specific fixed effects will likely affect our control variables such as ROA and $Equityratio$. In this case, using a standard OLS estimator will cause our estimates to be biased and inconsistent.

One way of getting rid of these firm-specific effects is by using a within-group transformation, also called the fixed effects estimator. This estimator transforms the equation to deviations from each variable's mean. This mean is calculated as the time average within each panel (group). Since time average of firm-specific effects a_i is just a_i itself, fixed effects are eliminated from the error term:

(4) $$NPLrate_{i,t} - \overline{NPLrate_i} = \sum_{j=1}^{4} \beta_j \left(NPLrate_{i,t-j} - \overline{NPLrate_i}\right) + \beta_5 \left(Competition_{i,t} - \overline{Competition_i}\right) + \beta_6 \left(Competition_{i,t}^2 - \overline{Competition_i^2}\right) + \sum_{n=1}^{M} \kappa_n \left(Control\ variable_{i,t} - \overline{Control\ variable_i}\right) + u_{i,t} - \overline{u_i}$$

where $\overline{X_i} = X_{i,t-1} + X_{i,t-2} + \cdots + X_{i,t-T}$ is the within-group mean of variable X.

Unfortunately, lagged dependent variables make the fixed effects estimator biased. This is apparent when considering that the fixed effects estimator transforms the equation to deviations from individual means. Since the within-group mean of the error term contains all realizations of the disturbances, it is likely to introduce endogeneity into the equation. $NPLrate_{i,t-1}$ will for instance be correlated with its corresponding error term $u_{i,t-1}$. Including more lags of this variable increases the endogeneity problem.

6.1.2 First Differencing in OLS

Another way of getting rid of the fixed effects is first differencing. Subtracting the first time lag from the contemporaneous value eliminates these effects, provided they are constant over time. The error term now contains one lag of the disturbance since $\Delta u_{i,t} = u_{i,t} - u_{i,t-1}$. This term is by definition correlated with the first term of $\Delta NPLrate_{i,t} = NPLrate_{i,t} - NPLrate_{i,t-1}$ and the coefficient on this variable will be biased when transforming to first differences. However, with first differencing we have the option of using an instrumental variable-approach. This will allow us to keep the lags and still achieve an unbiased model.

6.1.3 Instrumental variables

Anderson and Hsiao estimators can be applied to solve the endogeneity problem (Anderson & Hsiao, 1982). This estimator proposes using either the second lag in differences $\Delta NPLrate_{i,t-2}$ or the second lag in levels $NPLrate_{i,t-2}$ as instruments for the first differenced lagged dependent variable $\Delta NPLrate_{i,t-1}$, in a 2SLS instrument variable estimation. They both satisfy the instrumental variable relevance condition and are not endogenous in our first differenced specification. An additional advantage is that they are available internally in our dataset. We refer to this method as IV-regression.

Since we are able to use lagged values of already existing variables, we should also consider including more lags in order to improve the explanatory power of the first stage regression. If further lags give more information, including them will improve the efficiency of the model. However, for every lag we include as instruments we reduce the sample size by one time period. If we for instance instrument the differenced lagged dependent variable with five lags in levels, we would have to start the estimation in period 7. Consequently, this would cause us to lose 6 quarters of observations. Even though many of the banks in our dataset have over 90 quarters of observations, some have a substantially shorter lifespan. If we would like to use the information from these impermanent banks, we need to preserve time periods.

One way to bypass this tradeoff between model efficiency and sample size is the use of the General Method of Moments-estimator (GMM). By using an instrumental variables matrix, the GMM-estimator is able to use different instruments for different periods in the estimation. Earlier periods with fewer lags available are included in the estimation with as many lags as possible. This way, maximum 2 time periods are lost. Generally, GMM attempts to fit the model:

(5) $$y = x'B + \varepsilon$$

Where x is a column vector of k regressors, y and ε are random variables. By imposing *moment conditions* on the error terms for every instrumental variable it ensures consistency for the model. In general, the moment conditions require all instrumental variables to be uncorrelated with the error terms:

(6) $$E[\varepsilon|z] = 0$$

Where z is a column vector of j instruments. For N observations vectors x, y and z have corresponding matrices X, Y and Z. Our instrument matrix Z with j rows then has the following structure, following Arellano & Bond (1991):

(7) $$Z = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \cdots \\ NPLrate_{i,1} & 0 & 0 & 0 & 0 & 0 & \cdots \\ 0 & NPLrate_{i,1} & NPLrate_{i,2} & 0 & 0 & 0 & \cdots \\ 0 & 0 & 0 & NPLrate_{i,1} & NPLrate_{i,2} & NPLrate_{i,3} & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

By imposing the moments conditions to equal 0, GMM estimates regressors that are orthogonal to the errors. In other words: coefficients should be exogenous and unbiased. Imposing further moment conditions improves efficiency if the additional condition introduces more information.

The structure of the instrument matrix leaves the total number of instruments very large in panels with many time periods. There is no absolute rule of how many instruments is excessive, though it is recommended that they should be less than the number of groups (Roodman, 2009). Since many of the instrumental variables are recurring, we can collapse the matrix to save on a lot of instruments. This reduces the instrument number in the matrix drastically.

(8) $$Z = \begin{bmatrix} 0 & 0 & 0 & \cdots \\ NPLrate_{i,1} & 0 & 0 & \cdots \\ NPLrate_{i,1} & NPLrate_{i,2} & 0 & \cdots \\ NPLrate_{i,1} & NPLrate_{i,2} & NPLrate_{i,3} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

This matrix is used to obtain the GMM estimate:

(9) $$\hat{B}_A = (X'ZAZ'X)^{-1}\, X'ZAZ'Y$$

Where A is the weighting matrix assigning weight to the moment conditions.

6.1.4 Estimator decisions

Since the GMM estimator involves matrix calculations in multiple steps and complex instrument structures, it is crucial that we are careful when making choices about the construction of this estimator.

First we must decide on how many lags of the dependent variable to include in the instrument matrix. The ideal number of instruments is the one that explains the variation in $NPLrate_{i,t-1}$ which is exogenous to the differenced error term, and only this variation. There is a danger of overfitting the first step with too many lags. An overidentified model is not able to appropriately satisfy the moment conditions, which implies that the instruments cloud be endogenous with the errors.

We test the optimal lag structure using the Hansen test of overidentifying restrictions. To follow the Hansen-test mechanically is risky, since the test is weakened by an increasing number of instruments. 9 lags is recommended by the Hansen test, while 10 lags makes the model overidentified. As Roodman (2009) advises, we choose to be conservative, and employ 7 lags in order to avoid the risk of overfitting the model.

Our model is robust to variations in the number of instruments. This lag structure is appropriate for all our specifications. We choose to instrument our differenced variable in lagged levels to preserve one time period.

In order to calculate estimates that satisfy the moment conditions, GMM uses a matrix to weight the elements of the variance-covariance matrix. Estimation happens in either one or two steps. If our errors are identically and independently distributed, the weighting matrix A becomes the one from the 2SLS-estimator (Roodman, 2009). However, our error terms can both be heteroscedastic and can inhibit arbitrary patterns of covariance or autocorrelation within groups. This requires a weighting matrix that is based on the structure of the error terms. This is achieved by using initial error estimates from the two-step estimator to generate a weighting matrix giving efficient and robust estimate in the second step. In finite samples, this procedure can yield implausibly small standard errors, because the weighting matrix for the errors is calculated from their own variances and covariances, resulting in data mining (Roodman, 2009). Windmeijer (2005) finds a method for correcting this finite-sample inaccuracy by expressing the coefficient estimator as a function of the initial step weighting matrix. The corrected two-step estimator is more efficient and more accurate than the simpler one-step estimator. (Windmeijer, 2005)

Normal first difference transformation in general imposes a problem to data sets with gaps. Since two time observations are needed to construct one difference, gaps in observations will be magnified. GMM estimation provides the option of applying our orthogonal deviations rather than normal first differences to remedy this problem. Since Norwegian banks are required to report for every quarter of operation, our dataset does not suffer from many gaps in observations. We therefore apply normal first differences.

To summarize, we use a two-step estimation in normal first differences, with Windmeijer correction and robust standard errors clustered in individuals. We use 7 lags in the instrument matrix in addition to the other regressors also present as instruments.

6.2 Model diagnostics

In our regression tables, we list the results from estimating our model using both OLS, fixed effects, IV-regression and GMM. While only IV-regressions and GMM-regressions can be considered unbiased, the OLS and FE estimations provide an upper and lower bound for the endogenous first lag of the dependent variable. In OLS, the lagged dependent variable is positively correlated with the error term, resulting in an upward bias on the estimated coefficient. Correspondingly, the fixed effects coefficient has a downward bias, since the included group mean of the transformed lagged variable is negatively correlated with that of the transformed error term (Roodman, 2009). This provides a robustness check for the unbiased IV- and GMM- estimates.

6.2.1 Model consistency: Heteroskedasticity and autocorrelation

For OLS and FE regressions, we test for groupwise heteroskedasticity, modified for non-normality of the errors. In our IV- and GMM-regressions, we use the Breusch-Pagan/Godfrey/Cook-Weisberg-test for heteroskedasticity (Breusch & Pagan, 1979). For all our specifications, the test rejects the null hypothesis of homoscedasticity in the standard errors. We therefore report our results with clustered standard errors.

Another implication of the lag structure is the need to eliminate autocorrelation. Autocorrelation is problematic in GMM because the lagged instruments we are assuming to be exogenous are correlated with the differenced error term. By definition, the transformed error term $\Delta u_{i,t} = u_{i,t} - u_{i,t-1}$ is mathematically correlated with its lag $\Delta u_{i,t-1} = u_{i,t-1} - u_{i,t-2}$ via the shared term $u_{i,t-1}$. For an unbiased model, we therefore need to reject the null hypothesis of no first order autocorrelation, but not for second order autocorrelation. For all IV and GMM-specifications we report the Arellano-Bond-test (Arellano & Bond, 1991) for first- and second order autocorrelation labeled *m1* and *m2*, respectively.

We also report test statistics from the Hansen-tests for overidentifying restrictions for the GMM regressions, and Wald-tests for joint significance of the coefficients for all models.

7. Results

7.1 Using concentration indexes as measures of competition

The first set of regressions use concentration indexes C5 and HHI as measures of competition. **Table 2** shows regression results using different estimators in testing the relationship between our dependent variable $NPLrate$, and the C5 concentration index.

The results from using our preferred estimator, GMM, are listed in column 4. We include results from using OLS, FE and IV estimators in columns 1-3 to allow for robustness checks. Yearly and seasonal dummies are included in all regressions.

Both the OLS and FE estimators are expected to produce biased estimates of the lagged dependent variable. However, since these estimators are biased in opposite directions, they provide an upper and lower bound for the unbiased estimate. As a robustness test, Bond (2002) therefore suggests to compare the sum of coefficients for the lags of the dependent variable from GMM estimation with that of OLS and FE. The sum of coefficients on the lagged dependent variables is reported as SUM LDV at bottom of **Table 2**. We see from column 4 that the GMM estimator produces coefficients that lie within the boundaries indicated by OLS and FE estimations.

While both the IV and GMM estimators should result in unbiased estimates, GMM is expected to be more efficient. Comparing column 3 and 4, we see that these estimators produce similar estimates. Following Bond (2002), we use only one lag as an instrument for the lagged dependent variable in our IV estimator, to ensure that all results are estimated over the same sample period.

We test for first and second order autocorrelation in the instrumental variable and GMM estimations. The t-statistics for the m2 test indicate that we can reject the null hypothesis of second order autocorrelation. The Hansen test shows that the GMM estimation is not overidentified, indicating that the moment conditions are satisfied. These diagnostic tests indicate that our model is well specified.

Table 2 - Regression results using C5 as the competition variable

$NPLrate_{i,t} = \beta_0 + \sum_{j=1}^{4}\beta_j(NPLrate_{i,t-j}) + \beta_5 C5_t + \beta_6 C5_t^2 + \sum_{n=1}^{M}\kappa_n(Control\ variable_{i,t,n}) + \varepsilon_{i,t}$

Variables	(1) OLS	(2) FE	(3) IV-reg	(4) GMM
Competition variable				
$C5_t$	-1.0774***	-0.9834***	-0.8612**	-0.8264**
	(0.3232)	(0.3107)	(0.3377)	(0.3377)
$C5^2_t$	0.0085***	0.0077***	0.0067**	0.0064**
	(0.0027)	(0.0026)	(0.0028)	(0.0028)
Lagged dependent variable				
$NPLrate_{i,t-1}$	0.5675***	0.5209***	0.5939***	0.5708***
	(0.0307)	(0.0285)	(0.0535)	(0.0419)
$NPLrate_{i,t-2}$	0.1937***	0.1722***	0.2013***	0.1980***
	(0.0258)	(0.0251)	(0.0293)	(0.0271)
$NPLrate_{i,t-3}$	0.0613***	0.0485***	0.0576***	0.0555***
	(0.0179)	(0.0179)	(0.0219)	(0.0166)
$NPLrate_{i,t-4}$	0.0658***	0.0515***	0.0372*	0.0312**
	(0.0165)	(0.0165)	(0.0214)	(0.0138)
Control Variables				
$GDPgrowth_{t-1}$	-0.0500***	-0.0478***	-0.0145	-0.0246
	(0.0168)	(0.0164)	(0.0192)	(0.0179)
$GDPgrowth_{t-2}$	-0.0563***	-0.0544***	-0.0084	-0.0155
	(0.0155)	(0.0150)	(0.0179)	(0.0172)
$GDPgrowth_{t-3}$	-0.1346***	-0.1294***	-0.0739***	-0.0807***
	(0.0151)	(0.0146)	(0.0175)	(0.0171)
$GDPgrowth_{t-4}$	-0.0369***	-0.0356***	-0.0144	-0.0174
	(0.0138)	(0.0134)	(0.0154)	(0.0153)
$ROA_{i,t}$	-0.1497**	-0.1567**	-0.0941	-0.0940
	(0.0578)	(0.0648)	(0.0700)	(0.0696)
$Marketshare_{i,t}$	-0.0088***	0.0197	0.0253	0.0374
	(0.0030)	(0.0363)	(0.0674)	(0.0687)
$Equityratio_{i,t}$	0.0023	-0.0049	0.0474	0.0494
	(0.0032)	(0.0112)	(0.0432)	(0.0451)
Observations	11948	11948	11948	11948
Sum LDV	0.8884	0.7932	0.8900	0.8555
Seasonal dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
1st order AC - m1			-7.598	-7.284
2nd order AC - m2			-0.234	-0.584
Wald test	0.000	0.000	0.000	0.000
Hansen test				0.409

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the ratio of non-performing loans to total loans of bank *i* at time *t* ($NPLrate_{i,t}$). C5 is a market concentration index, calculated as the combined market shares in the loans market for the 5 largest banks at time t. GDP_t is the quarterly GDP growth rate at time *t*. $ROA_{i,t}$, is return of assets of bank *i* at time *t*. $Marketshare_{i,t}$ is the market share in the loans market of bank *i* at time *t*. $Equityratio_{it}$ is defined as the amount of equity over total assets for bank *i* at time *t*. m_1 and m_2 show t-values of the Arrelano-Bond test for first- and second order autocorrelation. We report p-values of the Wald-test, which tests for joint significance of the estimated coefficients. The Hansen test tests the model for overidentification. Clustered standard errors in parentheses.

The estimated coefficients on the lags of the dependent variable are all significant and positive. The coefficient on the first lag is 0.59, confirming that the level of non-performing loans that banks hold in their balance is persistent.

The negative signs on the $GDPgrowth$ variables confirm that increased economic growth in previous quarters decreases the rate of non-performing loans. However, the only significant term is the third lag of $GDPgrowth$. This indicates that it takes three quarters for a change in GDP growth to have a significant impact on the ability to service debt in the economy.

Our bank-specific control variables ROA, $Marketshare$ and $Equityratio$ turn out insignificant in explaining non-performing loan rates. This may indicate that the majority of differences between banks are controlled for when removing fixed effects.

Our main relationship of interest is of how concentration affects the riskiness of the banks loan portfolio. The GMM estimation finds a significant non-linear relationship between the C5 concentration index and non-performing loan rates. The estimated linear coefficient is negative while the coefficient on the squared term is positive, both significant on the 5% level. The inflection point is 64.3, which lies within the range of observed values for the C5 concentration index.

We find similar results when applying a different concentration measure to proxy for competition: the HHI concentration index. Results for these regressions are summarized in **Table 3**. The linear term is significantly negative at the 5% level, and the squared term is significantly positive at the 10% level. The inflection point is 0.17, which is also the maximum value for HHI observed over our sample period. The model diagnostics and the significance of control variables remains the same when we use a different concentration index.

These findings support a U-shaped relationship between concentration and the riskiness of the banks' loan portfolios. For low levels of market concentration, increases in concentration has a negative effect on non-performing loan rates. Past the inflection point, this relationship is reversed; higher market concentration increases non-performing loan rates.

Table 3 - Regression results using HHI as measure of competition

$$NPLrate_{i,t} = \beta_0 + \sum_{j=1}^{4}\beta_j\left(NPLrate_{i,t-j}\right) + \beta_5 HHI_t + \beta_6 HHI_t^2 + \sum_{n=1}^{M}\kappa_n(\,Control\ variable_{i,t,n}) + \varepsilon_{i,t}$$

Variables	(1) OLS	(2) FE	(3) IV-reg	(4) GMM
Competition variable				
HHI_t	-39.0500***	-37.9957***	-29.3052**	-28.9355**
	(12.3319)	(12.0087)	(14.2669)	(14.3092)
HHI^2_t	115.5277**	113.1376**	84.5719*	85.0439*
	(45.8119)	(44.7510)	(51.3251)	(51.5124)
Lagged dependent variable				
$NPLrate_{i,t-1}$	0.5669***	0.5203***	0.5823***	0.5603***
	(0.0306)	(0.0284)	(0.0519)	(0.0409)
$NPLrate_{i,t-2}$	0.1931***	0.1717***	0.1963***	0.1945***
	(0.0258)	(0.0252)	(0.0292)	(0.0272)
$NPLrate_{i,t-3}$	0.0620***	0.0490***	0.0556***	0.0547***
	(0.0178)	(0.0178)	(0.0216)	(0.0163)
$NPLrate_{i,t-4}$	0.0662***	0.0518***	0.0364*	0.0312**
	(0.0164)	(0.0165)	(0.0213)	(0.0137)
Control Variables				
$GDPgrowth_{t-1}$	-0.0559***	-0.0528***	-0.0162	-0.0271
	(0.0166)	(0.0163)	(0.0191)	(0.0177)
$GDPgrowth_{t-2}$	-0.0578***	-0.0555***	-0.0085	-0.0158
	(0.0159)	(0.0155)	(0.0181)	(0.0174)
$GDPgrowth_{t-3}$	-0.1303***	-0.1249***	-0.0706***	-0.0781***
	(0.0149)	(0.0144)	(0.0175)	(0.0170)
$GDPgrowth_{t-4}$	-0.0345**	-0.0332**	-0.0122	-0.0158
	(0.0139)	(0.0135)	(0.0155)	(0.0153)
$ROA_{i,t}$	-0.1509***	-0.1580**	-0.0967	-0.0955
	(0.0579)	(0.0649)	(0.0695)	(0.0691)
$Marketshare_{i,t}$	-0.0088***	0.0195	0.0232	0.0351
	(0.0030)	(0.0360)	(0.0662)	(0.0672)
$Equityratio_{i,t}$	0.0025	-0.0044	0.0490	0.0508
	(0.0032)	(0.0112)	(0.0426)	(0.0444)
Observations	11948	11948	11948	11948
Sum LDV	0.8882	0.7929	0.8706	0.8407
Seasonal dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
1st order AC - m1			-7.542	-7.212
2nd order AC - m2			-0.249	-0.646
Wald test	0.000	0.000	0.000	0.000
Hansen test				0.374

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Notes: The dependent variable is the ratio of non-performing loans to total loans of bank *i* at time *t* ($NPLrate_{i,t}$). C5 is a market concentration index, calculated as the combined market shares in the loans market for the 5 largest banks at time t. GDP_t is the quarterly GDP growth rate at time *t*. $ROA_{i,t}$, is return of assets of bank *i* at time *t*. $Marketshare_{i,t}$ is the market share in the loans market of bank *i* at time *t*. $Equityratio_{i,t}$ is defined as the amount of equity over total assets for bank *i* at time *t*. m_1 and m_2 show t-values of the Arrelano-Bond test for first- and second order autocorrelation. We report p-values of the Wald-test, which tests for joint significance of the estimated coefficients. The Hansen test tests the model for overidentification. Clustered standard errors in parentheses.

We wish to interpret both short-term and long-term effects of changes in concentration on non-performing loan rates. We calculate the long-run coefficients by assuming equilibrium, which is denoted $\widetilde{NPLrate_i}$:

(10) $\widetilde{NPLrate_i} = \beta_0 + \sum_{j=1}^{4} \beta_j \widetilde{NPLrate_i} + \beta_5 Competition_{i,t} + \beta_6 Competition_{i,t}^2 + \sum_{n=1}^{M} \kappa_n(Control\ variable_{i,t,n}) + \varepsilon_{i,t}$

Which can be rewritten as:

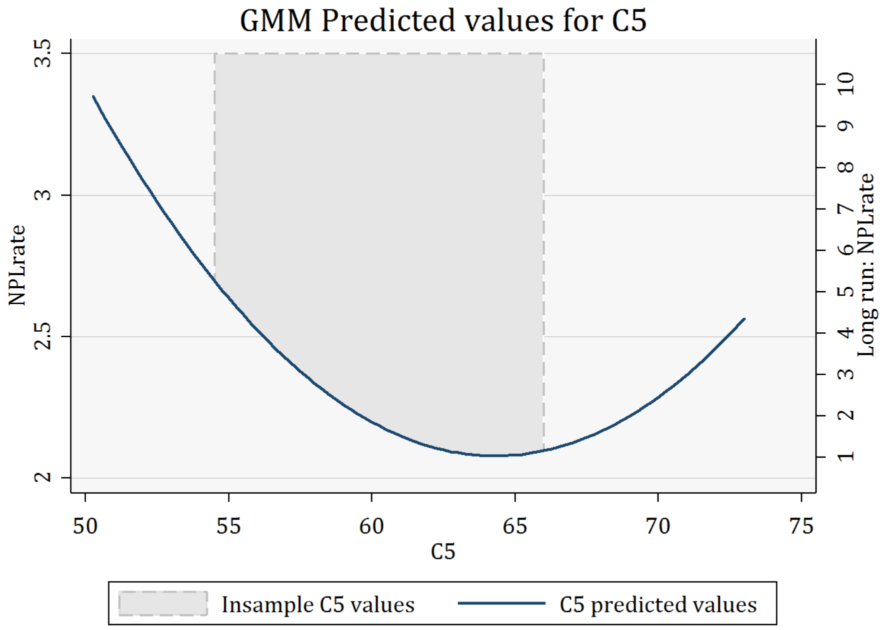
(11) $\widetilde{NPLrate_i} = \frac{1}{1-\sum_{j=1}^{4} \beta_j} \{\beta_0 + \beta_5 Competition_{i,t} + \beta_6 Competition_{i,t}^2 + \sum_{n=1}^{M} \kappa_n(Control\ variable_{i,t,n}) + \varepsilon_{i,t}\}$

The long-run coefficients are therefore obtained by dividing the short-run coefficients with $(1 - \sum_{j=1}^{4} \beta_j)$, which is 1 minus SUM LDV. For $C5$, the long-term coefficient on the linear term is $\hat{\beta}_5^{LR} = -5{,}72$ and $\hat{\beta}_6^{LR} = 0{,}044$ on the squared term. For HHI, these values are $\hat{\beta}_5^{LR} = -181{,}64$ and $\hat{\beta}_6^{LR} = 533{,}86$. While the short- and long-run coefficients differ in magnitude, the inflection points are the same.

Figure 6 and **Figure 7** illustrate the estimated relationships between non-performing loan rates and concentration measures $C5$ and HHI. The x-axis plots values of the relevant concentration index. Movement to the right along the x-axis implies increased concentration. The grey area represents the range of concentration values found in our sample. We use the y-axis to plot predicted values of $NPLrate$ in order to illustrate how a change in concentration will affect levels of non-performing loan rates. The left y-axis shows the short run effect of concentration changes on non-performing loan rates. The right y-axis plots values corresponding to the long run effect.

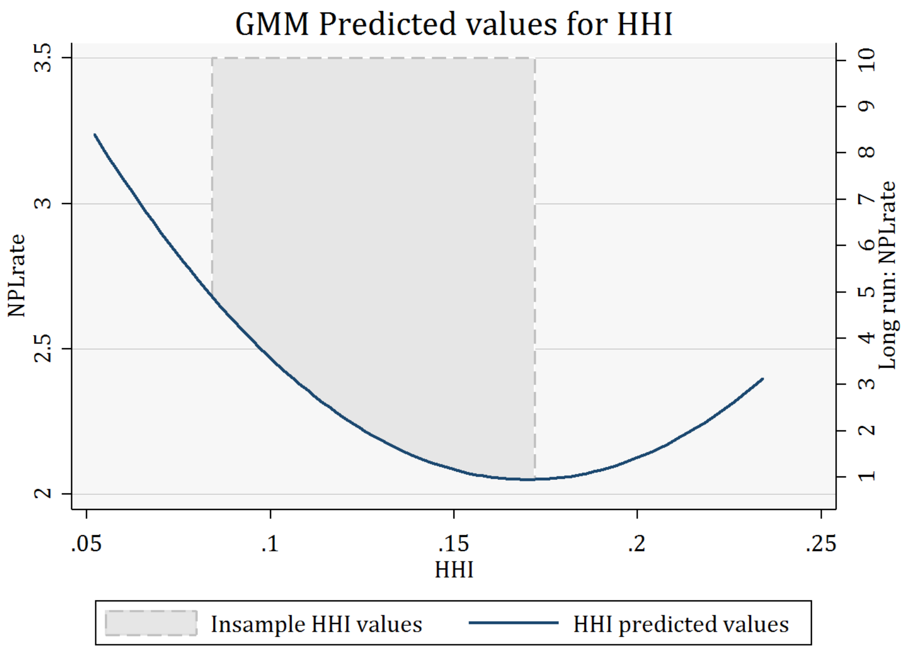
Constant terms and firm specific effects are removed with GMM estimation. Therefore, the levels of the y-axes in our graphs are normalized so that the average of the predicted values within the sample equals the $NPLrate$ variable average.

Figure 6



Note: The insample values are based on the full sample of the variable as provided in Appendix 2. Predicted values are based on estimations from regression (4) in **Table 2**.

Figure 7



Note: The insample values are based on the full sample of the variable as provided in Appendix 2. Predicted values are based on estimations from regression (4) in **Table 3**.

The U-shaped relationship illustrated in these figures supports the theoretical model proposed by Martinez-Miera and Repullo (2010), as discussed in the section 2. They suggest that only in markets with low levels of competition will increased competition reduce the riskiness of banks. This is in line with our findings, to the extent that concentration is an appropriate measure of competition.

The intuition behind this relationship, according to MMR, is that two opposing effects impact the relationship between competition and the risk profile of banks. On one hand, lower competition allows banks to operate with higher margins. This makes banks take less risk in order to protect their earnings. On the other hand, when interest rates become too high, loan customers are more likely to default on their payment obligations. This is referred to as the risk-shifting effect.

Within our sample range of $C5$, the effect of concentration on non-performing loan rates is mostly negative. The mean observation value for $C5$ is 59,8. For this concentration level, a percentage-point increase in the combined market share for the 5 largest banks reduces the $NPLrate$ by 0,06 percentage points in the short run. The long-run effect is a decrease of 0,44 percentage points.

The HHI variable has a mean value of 0,115, which is also below the inflection point. At this concentration level, the short-run effect of an increase of 0,01 in HHI is a 0,09 percentage point reduction in $NPLrate$. The long-run effect at this point is a decrease in $NPLrate$ of 0,58 percentage points.

The estimated inflection points for both HHI and $C5$ are relatively high compared to observed values over the sample period. This could imply that increases in concentration have for the most part contributed to reductions in non-performing loan rates for Norwegian banks. However, the level of concentration as measured by both C5 and HHI has exhibited a positive trend for the last 5 years. In fact, the concentration level in the last period of our sample (2014, Q4) is among the highest observed values of concentration for the last 20 years. While the last observed HHI index is still below the inflection point, the C5 index in this quarter is at the inflection point of 64,3. Our regression results therefore indicate that a continued positive trend in bank concentration will increase non-performing loan rates.

7.2 Using interest rate margin as the measure of competition

Table 4 reports the regression results using interest rate margins as the measure of competition. $IRmargin$ is calculated as of the difference between the average interest rate on loans and the 3-month NIBOR rate. The variable is included in the model as a two-period moving average.

We expect $IRmargin$ to be endogenous when included as a contemporaneous variable in our specification. One possible solution would be to instrument $IRmargin$ with lagged values of itself. However, instrumenting will produce a very large GMM instrument matrix, threatening the satisfaction of the moment conditions and the validity of the model. We therefore employ the second lag of the $IRmargin$ as the explanatory variable, which is assumed to be exogenous. Theoretically, this is also valid since it takes time for risky investments to develop into non-performing loans on banks' balance sheets. Regressions using the instrumented first lag produce similar results, although this specification is found to be overidentified.

Control variables are similar to those in the regressions using concentration indexes. The effect of GDP growth is negative in all periods, but only the third lag is significant at the 1% level. All firm-specific control variables are insignificant in explaining $NPLrate$. Both yearly and seasonal dummy variables are included in all regressions.

Model diagnostics show that the both GMM and IV-reg estimations are free from autocorrelation. The GMM model is not found to be overidentified by the Hansen test. As a robustness check, we see that the results from IV-reg in column 3 and GMM in column 4 are very similar. SUM LDV from both these regressions lie within the boundaries set by the OLS and FE regressions in column 1 and 2.

Table 4 - Regression results using interest rate margin as competition variable

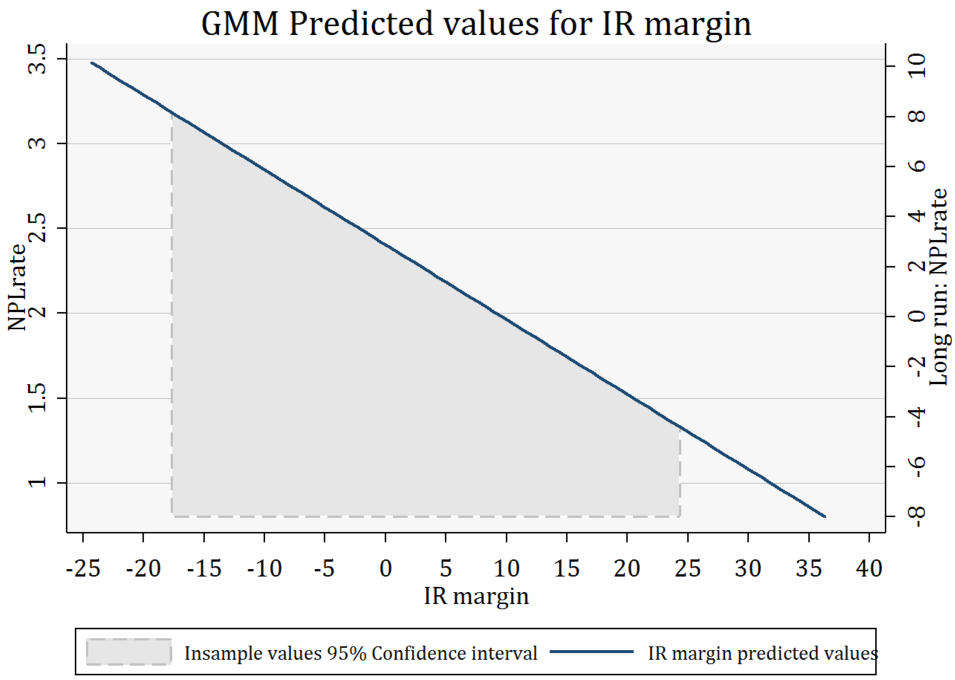
$$NPLrate_{i,t} = \beta_0 + \sum_{j=1}^{4} \beta_j (NPLrate_{i,t-j}) + \beta_5 IRmargin_{i,t-2} + \sum_{n=1}^{M} \kappa_n (Control\ variable_{i,t,n}) + \varepsilon_{i,t}$$

Variables	(1) OLS	(2) FE	(3) IV-reg	(4) GMM
Competition variable				
$IRmargin_{i,t-2}$	0.0277^{**}	-0.0050	-0.0438^{***}	-0.0442^{***}
	(0.0140)	(0.0104)	(0.0169)	(0.0171)
Lagged dependent variable				
$NPLrate_{i,t-1}$	0.5645^{***}	0.5197^{***}	0.5670^{***}	0.5654^{***}
	(0.0301)	(0.0283)	(0.0499)	(0.0399)
$NPLrate_{i,t-2}$	0.1914^{***}	0.1719^{***}	0.1920^{***}	0.1918^{***}
	(0.0256)	(0.0251)	(0.0292)	(0.0273)
$NPLrate_{i,t-3}$	0.0593^{***}	0.0480^{***}	0.0539^{**}	0.0547^{***}
	(0.0181)	(0.0179)	(0.0216)	(0.0165)
$NPLrate_{i,t-4}$	0.0673^{***}	0.0532^{***}	0.0362^{*}	0.0342^{**}
	(0.0165)	(0.0165)	(0.0212)	(0.0136)
Control Variables				
$GDPgrowth_{t-1}$	-0.0739^{***}	-0.0664^{***}	-0.0242	-0.0280^{*}
	(0.0156)	(0.0155)	(0.0179)	(0.0170)
$GDPgrowth_{t-2}$	-0.0678^{***}	-0.0686^{***}	-0.0258	-0.0291^{*}
	(0.0156)	(0.0149)	(0.0170)	(0.0163)
$GDPgrowth_{t-3}$	-0.1254^{***}	-0.1294^{***}	-0.0859^{***}	-0.0898^{***}
	(0.0147)	(0.0139)	(0.0177)	(0.0170)
$GDPgrowth_{t-4}$	-0.0286^{**}	-0.0337^{**}	-0.0196	-0.0208
	(0.0139)	(0.0134)	(0.0152)	(0.0151)
$ROA_{i,t}$	-0.1744^{***}	-0.1618^{**}	-0.0997	-0.0997
	(0.0602)	(0.0656)	(0.0693)	(0.0683)
$Marketshare_{i,t}$	-0.0085^{***}	0.0166	0.0142	0.0202
	(0.0028)	(0.0355)	(0.0643)	(0.0639)
$Equityratio_{i,t}$	0.0015	-0.0039	0.0517	0.0546
	(0.0033)	(0.0112)	(0.0417)	(0.0420)
Observations	11941	11941	11941	11941
Sum LDV	0.8825	0.7928	0.8491	0.8461
Seasonal dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
1st order AC - m1			-7.500	-7.344
2nd order AC - m2			-0.361	-0.221
Wald test	0.000	0.000	0.000	0.000
Hansen test				0.868

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the ratio of non-performing loans to total loans of bank i at time t ($NPLrate_{i,t}$). $IRmargin_{i,t-2}$ is the interest rate margin of bank i at time $t-2$. IRmargin is calculated as the difference between the ratio of gross interest income over gross total loans of bank i at time t, and the 3-month Norwegian Inter Bank Offer Rate at time t. GDP_t is the quarterly GDP growth rate at time t. $ROA_{i,t}$, is return of assets of bank i at time t. $Marketshare_{it}$ is the market share in the loans market of bank i at time t. $Equityratio_{i,t}$ is defined as the amount of equity over total assets for bank i at time t. m_1 and m_2 show t-values of the Arrelano-Bond test for first- and second order autocorrelation. We report p-values of the Wald-test, which tests for joint significance of the estimated coefficients. The Hansen test tests the model for overidentification. Clustered standard errors in parentheses.

Figure 8



Note: The insample values are based on the full sample of the variable as provided in Appendix 2. Predicted values are based on estimations from regression (4) in **Table 4**.

Figure 8 graphs the predicted values for $NPLrate$ at different levels of $IRmargin$. The left y-axis plots the impact on $NPLrate$ in the short run, while the right y-axis plots the long-run effect. The grey area represents a 95% confidence interval for the values of $IRmargin$ in our sample.

We do not find a significant non-linear relationship between the interest rate margin and non-performing loan rates. However, we find a negative linear relationship, significant at the 5% level. The estimated coefficient implies that a 1 percentage point increase in a bank's interest rate margin decreases its non-performing loan rate by 0,044 percentage points in the short run. The long run coefficient equals $\hat{\beta}_5^{LR} = \frac{0{,}044}{(1-0{,}8461)} = 0{,}29$ so that an equal permanent change in the interest rate margin decreases the non-performing loan rate by 0,29 percentage points.

These findings support the franchise value hypothesis, which proposes that reductions in interest rate margins increase banks' risk taking. When interest margins are low, banks have a lower opportunity cost of going bankrupt and will be more inclined to make loans to riskier customers (Hellmann, Murdock, & Stiglitz, 2000). We should keep in mind that interest rate margins only capture competitive behavior that is reflected in market interest rates. If the banks compete using other strategic variables like loan volume or marketing, the interest rate margin will not capture all competitive behavior. Still, our findings support the existence of a risk-motivating incentive at falling interest rate margins.

7.3 Using H-statistic as the measure of competition

Table 5 reports the regression results using the rolling-window H-statistic to measure competition. Since the H-statistic is calculated from markup elasticities, we also lag this measure two periods to avoid endogeneity. The calculation of $Hstat$ is explained in section 4.2.4 with further discussion in Appendix 1.

Model diagnostics reveal that both GMM and IV-reg estimations are free from autocorrelation. The GMM-model is not overidentified by the Hansen test. SUM LDV from IV-reg and GMM regressions in column 3 and 4 lie within the boundaries set by OLS and FE.

Control variables remain unchanged in significance from previous regressions; only the third lag of $GDPgrowth$ is significant at the 1% level. The first two lags of GDP growth and $Marketshare$ switch signs to being positive, although the coefficients are still not significant. The Wald-test for joint significance rejects the null hypothesis of all-zero coefficients.

We find a positive linear relationship between $Hstat$ and $NPLrate$ with a coefficient of 0,2491, although only significant at the 10% level. Theoretically, a higher number of the H-statistic indicates stronger competition. Our findings therefore indicate that a rise in competition increases the rate of non-performing loans for all the banks in the loan market. An increase from 0 – associated with monopolistic competition, to 1 – associated with perfect competition, increases the average non-performing loan rate for the whole market by 0,2491 percentage points. The long run coefficient equals $\hat{\beta}_5^{LR} = \frac{0,2491}{(1-0,8389)} = 1,55$, implying that perfect competition on average is associated with a 1,55 percentage points higher $NPLrate$, compared to the case of monopoly.

Table 5 - Regression results using H-statistic as competition variable

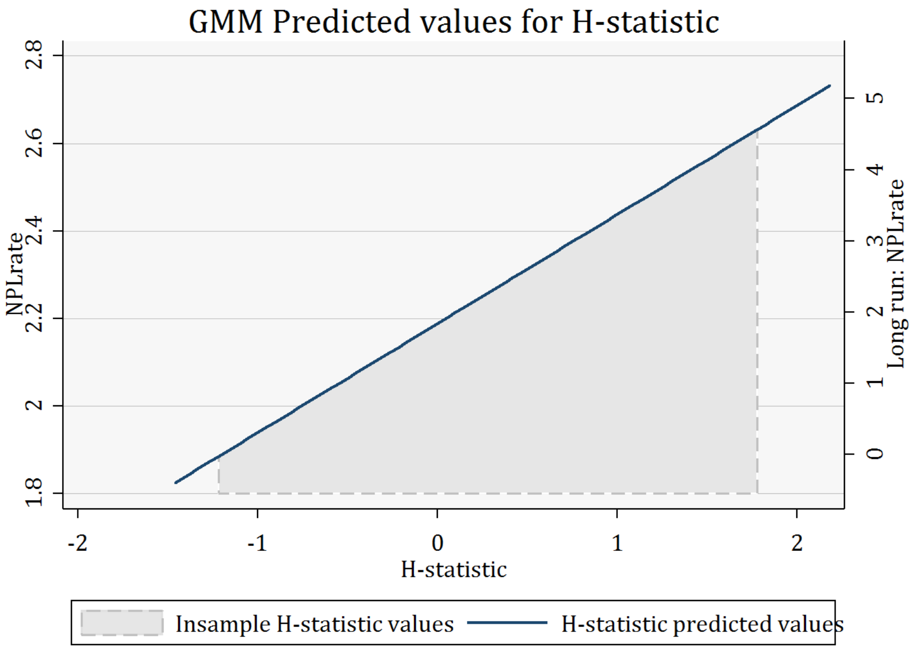
$$NPLrate_{i,t} = \beta_0 + \sum_{j=1}^{4}\beta_j\left(NPLrate_{i,t-j}\right) + \beta_5 Hstat_{t-2} + \sum_{n=1}^{M}\kappa_n(\,Control\ variable_{i,t,n}) + \varepsilon_{i,t}$$

Variables	(1) OLS	(2) FE	(3) IV-reg	(4) GMM
Competition variable				
$Hstat_{t-2}$	0.3111***	0.3346***	0.2406*	0.2491*
	(0.0928)	(0.0906)	(0.1357)	(0.1362)
Lagged dependent variable				
$NPLrate_{i,t-1}$	0.5551***	0.5046***	0.5440***	0.5562***
	(0.0326)	(0.0304)	(0.0409)	(0.0390)
$NPLrate_{i,t-2}$	0.1897***	0.1648***	0.1811***	0.1850***
	(0.0274)	(0.0263)	(0.0293)	(0.0297)
$NPLrate_{i,t-3}$	0.0702***	0.0517***	0.0581**	0.0650***
	(0.0184)	(0.0185)	(0.0235)	(0.0188)
$NPLrate_{i,t-4}$	0.0703***	0.0467***	0.0282	0.0326**
	(0.0180)	(0.0177)	(0.0216)	(0.0146)
Control Variables				
$GDPgrowth_{t-1}$	-0.0579***	-0.0530***	-0.0184	-0.0182
	(0.0177)	(0.0172)	(0.0199)	(0.0194)
$GDPgrowth_{t-2}$	-0.0508***	-0.0466***	-0.0042	-0.0073
	(0.0170)	(0.0165)	(0.0209)	(0.0206)
$GDPgrowth_{t-3}$	-0.1253***	-0.1177***	-0.0594***	-0.0602***
	(0.0147)	(0.0142)	(0.0189)	(0.0185)
$GDPgrowth_{t-4}$	-0.0379***	-0.0359***	-0.0131	-0.0128
	(0.0133)	(0.0129)	(0.0151)	(0.0151)
$ROA_{i,t}$	-0.1580**	-0.1615**	-0.0590	-0.0450
	(0.0639)	(0.0746)	(0.0799)	(0.0780)
$Marketshare_{i,t}$	-0.0098***	-0.0055	0.0073	-0.0007
	(0.0035)	(0.0282)	(0.0660)	(0.0635)
$Equityratio_{i,t}$	0.0030	0.0012	0.0341	0.0353
	(0.0029)	(0.0125)	(0.0438)	(0.0433)
Observations	11279	11279	11279	11279
Sum LDV	0.8853	0.7678	0.8114	0.8389
Seasonal dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
1st order AC - m1			-7.475	-7.267
2nd order AC - m2			-0.094	0.236
Wald test	0.000	0.000	0.000	0.000
Hansen test				0.711

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable the is ratio of non-performing loans to total loans of bank *i* at time *t* ($NPLrate_{i,t}$). $Hstat_{t-2}$ is the H-statistic, a competitive measure of the loans market at time *t*. It estimated as the sum of elasticities of interest income to input prices for all banks at time *t-2*. GDP_t is the quarterly GDP growth rate at time *t*. ROA_{it}, is return of assets of bank *i* at time *t*. $Marketshare_{i,t}$ is the market share in the loans market of bank *i* at time *t*. $Equityratio_{i,t}$ is defined as the amount of equity over total assets for bank *i* at time *t*. m_1 and m_2 show t-values of the Arrelano-Bond test for first- and second order autocorrelation. We report p-values of the Wald-test, which tests for joint significance of the estimated coefficients.
The Hansen test tests if the model is overidentified. Clustered standard errors in parentheses.

Figure 9



Note: The insample values are based on the full sample of the variable as provided in Appendix 2. Predicted values are based on estimations from regression (4) in **Table 5**.

Figure 9 plots the predicted values for *NPLrate* for given levels of *Hstat*. The left y-axis represents the short run effect, while the right y-axis represents the long run effect. These findings also support the competition-fragility view that competition hurts financial stability. On average, stronger competitive behavior increases non-performing loan rates for all banks in the market.

We should use caution when interpreting the validity of these findings. The H-statistic has shown to be an unreliable measure of competition, since ability to pass through cost changes to revenue could be affected by other factors, such as strategic pricing or differentiation. Therefore, the findings more accurately reflect the relationship between banks' ability to pass through cost changes to the market and non-performing loan rates. Although the H-statistic is an unreliable absolute measure of competition, we are mainly interested the effect of competitive changes on loan risk. If the variation in the H-statistic over time represents valid changes in the competitive environment, the findings are valid for describing market mechanisms.

8. Conclusion

This thesis has summarized important findings in the literature on the relationship between competition in banking markets and financial stability, and aimed to provide an empirical analysis of this topic for the Norwegian banking market. Through econometric analysis, we find that our competition variables have a significant impact on the banks' rate of non-performing loans. This suggests that theories found in the literature can help explain how Norwegian banks react to competition.

We find a non-linear relationship between market concentration and banks' rates of non-performing loans. For low levels of concentration in the banking market, increased concentration contributes to reduce non-performing loan rates. Past a certain level of concentration, this relationship is reversed. Our findings therefore imply that in order to minimize non-performing loan rates, there is an optimal level of market concentration. Regression results using both HHI and C5 indexes conclude that the Norwegian banking market today is close to this optimal level. Our findings suggest a continued increasing trend in concentration will contribute to higher non-performing loan rates.

Using the interest rate margin as a competitive measure, we find a linear negative relationship between the interest rate margin and our risk measure. Higher interest rate margins are found to reduce the rates of non-performing loans over our sample period. Provided that the interest rate margin measures competitive behavior, these results imply that competition increases the riskiness of the banks' loan portfolios.

A linear positive relationship is found between the H-statistic and non-performing loan rates. The H-statistic is most commonly employed to distinguish between levels of competition, rather than being interpreted on a continuous scale. Our findings indicate that behavior in line with perfect competition in the long run increases the rate of non-performing loans with 1,5 percentage points, compared to the case of monopoly.

Although the H-statistic is a commonly applied measure of competition in empirical banking studies, it is controversial due to its reliance on a series of strict assumptions. It has also been shown to be unreliable in several theoretical settings (Spierdijk & Shaffer, 2015).

Both the interest rate margin and the H-statistic provide results that are in line with the franchise value hypothesis. First proposed in a seminal study by Keeley (1990), this theory emphasizes that stronger competition put banks' margins under pressure, reducing the alternative cost of going bankrupt. This creates incentives for the banks to increase the risk of their investments.

The non-linear relationship found when using concentration as a competitive measure supports another theoretical model, proposed by Martinez-Miera and Repullo (2010). Their argument is that market power increases incentives for banks to avoid bankruptcy, but also reduces the incentives and ability of borrowers to repay their loans.

To summarize, our findings provide support for the existence of a negative relationship between competition in the banking market and the riskiness of the banks' loan portfolios. This may imply that banks do in fact take more risk when their market power is reduced. Our findings also indicate that to the extent that concentration is an appropriate measure of competition, this relationship is reversed when the market becomes highly concentrated.

In this thesis, we have focused on the effect of competition on the rate of non-performing loans. It is important to keep in mind that the total risk for the bank may react differently. For instance, reducing risk from other activities could offset increased loan portfolio risk. Also, if competition does in fact increase the ratio of defaulting loans, this does not necessarily outweigh the welfare gains produced by competition.

Appendix 1: Calculation of the H-statistic

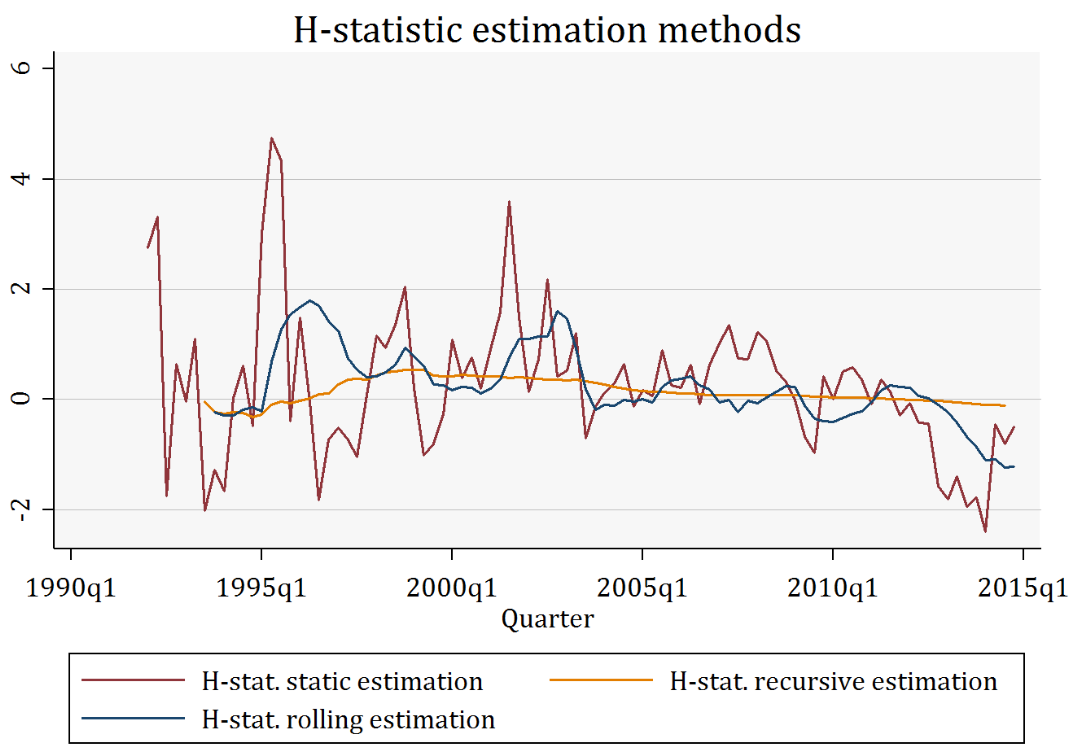
8.1.1 Estimator

According to Bikker, Shaffer and Spierdijk (2012), the preferred estimator for consistent H-statistic calculation is the within-group estimator. Pooled OLS is found to yield the same results, though it is less efficient. After attempting several different specifications and estimators, we conclude that pooled OLS is the only estimator yielding non-erratic results for our data set. The within-group estimator calculates values far outside the theoretical range of the H-statistic. We therefore apply the pooled OLS estimator with robust standard errors in our calculations.

8.1.2 Estimation method

Figure 10 displays the estimates from 3 different estimation methods: static, recursive and rolling window estimate.

Figure 10



The figure shows that static estimation of the H-statistic yields quite volatile results, This is in line with the statement by Bikker and Spierdijk (2008) that static estimation yield erratic results. The recursive estimates lie between the theoretical values, but provide little variation in the competitive measure. Since this estimation method uses all previous time periods to calculate todays' competition, recent information weighs relatively less. The rolling window estimation is mostly within the theoretical values, and provides enough variation in the competitive measure. Including an additional time period to the rolling window estimate reduces the error of the estimate but also omits one time period of observations for the analysis. A parsimonious rolling window of 8 quarters gives consistent estimates. Our H-statistic estimate is therefore calculated using a window estimate starting in period 8.

Appendix 2: Summary statistics table

Table 6: Summary statistics for the entire sample of each variable

	Mean	Observations	Median	Min	Max	St. dev
NPLrate	2.259	13033	1.52	0.000064	25.5	2.421
C5	59.80	15732	60.16	54.5	66.1	2.632
HHI	0.115	15732	0.11	0.082	0.17	0.024
GDPgrowth	0.733	15732	0.60	-2.28	4.23	0.987
Marketshare	0.689	13251	0.09	0.00025	38.4	2.740
ROA	0.304	13251	0.30	-2.00	2.11	0.296
Equityratio	10.33	13251	9.83	-45.4	64.3	4.344
NIBOR	4.736	13349	4.46	1.48	15.8	2.601
IRmargin	2.968	13315	2.64	-24.6	30.7	2.368
H-statistic	0.239	14535	0.18	-1.23	1.79	0.654

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