

NHH



Consequences of Competition and Proximity on the Stability in Banking

*Are there Cyclical Tendencies in Risk Taking, through Distant Lending, in the
Corporate Loan Market in Norway?*

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Abstract

In this thesis, we attempt to provide evidence on how competition in the corporate loan market in Norway affects banks' risk taking, and hence the financial stability, through distant lending over the business cycle. We use comprehensive data from the Norwegian banking market, containing annual information on 169 banks and approximately 136 000 firms over the period 1997 to 2013. Our analysis provides ambiguous results on whether there is cyclical variation in lending distances, and collectively we cannot conclude that there is a clear relationship between business cycles and loan distances. Furthermore, we cannot conclude that increased lending distance is associated with increased risk. Since we do not find such a relationship, we do not consider it beneficial to run our last model investigating the effect of competition on banks' risk taking, through distant lending. Regardless of whether increased competition leads to increased lending distances, it is not possible to measure whether competition affect banks' risk taking, as we cannot use distance as an adequate proxy for the risk associated with a loan. Hence, we cannot conclude that competition in the Norwegian banking sector has a negative impact on financial stability through distant lending.

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1. Introduction

1.1. Motivation and Purpose

The main purpose of this thesis is to examine how competition in the corporate loan market in Norway affects banks' risk taking, through distant lending over the business cycle. A recent study by Granja, Leuz & Rajan (2019) in the United States (U.S.) finds that lending distance, i.e. the average distance between the borrowing firm and the lending bank, is cyclical, lengthening considerably during an economic upturn and shortening again during the following downturn. Furthermore, they find that distant lending in boom is, on average, riskier and hence amounts to the risk taking by the bank. These findings are consistent with the characteristics of a bank pursuing a procyclical lending policy. A procyclical lending policy might entail that banks take on more risk in an economic upturn (Finansdepartementet, 2012). If this is the case, it may contribute to financial instability by reinforcing a cyclical upturn through looser credit supply and increased risk appetite during boom times. Conversely, banks' lending policy could amplify a downturn through tightening of their credit practices in a bust.

However, Granja et al. (2019) find that not all lenders behave in the same way over the cycle. Their findings suggest that banks that are exposed to greater competitive pressure, i.e. that several banks are competing for business in an area, have higher risk tolerance and willingness to make loans at greater distances in the midst of a boom. In areas with greater competition, banks may give out loans after all safe loans are made. At the same time, they find that banks that are diversified across regions with differing degrees of competition, do not show the same risk-taking behavior. This suggests that competition is an important explanatory factor of the cyclical tendencies in distant lending. The theory on the effect of competition on banks' lending behavior and stability is however ambiguous (Vives, 2016). On one hand, diminishing market powers and lower profit margins may incentivize banks risk-taking. On the other hand, better lending conditions, e.g. lower interest rates, may attract safer borrowers.

In Norway, the Norwegian banking crisis, in the late 1980s and early 1990s, gives insight into the consequences of regulation and competition in the banking sector (Moe, Solheim, & Vale, 2004). Heavy regulations on banks credit supply were lifted in 1984 and 1985, which resulted in a lending boom as banks fought for market shares. The new competitive environment led to banks expanding into new geographical and business areas of which they had limited

knowledge. Along with insufficient regulations from the authorities, this resulted in excessive operational and credit risk (Moe, Solheim, & Vale, 2004).

In the aftermath of the banking crisis more attention was placed on risk management and new methods were employed in order to calculate appropriate risk premiums in loan rates (Steigum & Thøgersen, 2013). In addition, there was an increased focus on the importance of cooperation between Finanstilsynet (*the Financial Supervisory Authority*), the Ministry of Finance (*Finansdepartementet*) and Norges Bank (*the Central Bank of Norway*), as well as stricter regulation of the banking sector. These measures are argued to have contributed to a relatively robust banking system today. In addition, they contributed to the moderate financial recession in Norway during the financial crisis in 2008, where the consequences were small in an international perspective (Grytten & Hunnes, 2016). However, Finanstilsynet's (2019) Risk Outlook report in June, shows that debt levels of non-financial firms in Norway, measured as a share of GDP, are at a historically high level in 2019. The same development is evident internationally, where debt burden is high in several countries with increasing public and private debt (Finanstilsynet, 2019). Furthermore, an increasing proportion of corporate loans are taken out by non-financial firms with weak financial positions and earnings.

Norges Bank, together with the Ministry of Finance, attempt to counteract increasing debt levels in Norway through instruments such as countercyclical monetary policy, countercyclical capital buffer and stricter lending regulations (Norges Bank, 2019d). This is essential to ensure a stable banking system and to prevent deep recessions in Norway. In order for these measures to have the desired effect, it is necessary to investigate whether competition leads to procyclical lending behavior through distant lending in Norway, as observed in other countries like the U.S. (Granja, Leuz, & Rajan, 2019). If such behavior is detected in Norway, it might lead to excessive risk taking and less stability in the banking system.

Competition is known to enhance efficiency through increased productivity and more effective allocation of resources (Vives, 2016). However, competition in the banking sector has been perceived with suspicion, as it also appears to lead to excessive risk taking, credit overexpansion and vigorous growth, in addition to bank misconduct, when not properly regulated. Since these negative aspects of competition in the banking sector might have a devastating effect on the economy, both domestically and internationally, this is a topic which has been widely debated. It is also the reason why the banking sector is strictly regulated compared to other sectors. There is, however, a trade-off between competition and financial

stability as competition has several beneficial aspects and it is not desirable to regulate unnecessarily (Vives, 2016).

With this in mind we want to investigate how competition affect banks' risk taking, and hence the stability, in the corporate loan market in Norway. In addition, we want to investigate whether distance between the lending bank and borrowing firm is of economic importance in this market. The answers to these questions might shed light on the financial health of the banking industry in Norway.

1.2. Research Question

To investigate the relationship between competition and banks' lending behavior, we propose the following research question:

Does competition in the corporate loan market in Norway affect banks' risk taking, through distant lending over the business cycle?

We attempt to answer this question by regressing measures of firm risk, lending distances, business cycles and competition.

1.3. Outline

This master thesis will be organized as follows: In **Section 2** we present an overview of the Norwegian bank sector, the corporate market in Norway and the financial stability in the Norwegian banking sector. **Section 3** review relevant theoretical and empirical literature investigating the relationship between competition, lending distance, business cycle fluctuations and risk. **Section 4** presents our empirical strategy. **Section 5** gives a description of the treatment of our dataset and the construction of our most relevant variables. In **Section 6** we present some descriptive statistics of our sample and lending distance in particular. In **Section 7** we present the results from our regressions, while in **Section 8** we present some possible sources of divergence from previous findings. Finally, our concluding remarks are included in **Section 9**.

2. Institutional Background

2.1. Characteristics of the Norwegian Banking Sector

Compared to other Western European countries, the Norwegian banking sector is small in terms of value added, with total assets amounting to only two times GDP (Norges Bank, 2019a). In comparison, Swedish, French and Dutch banks' total assets are more than three times GDP. According to Norges Bank, one important reason for this is that Norwegian banks mainly lend to domestic customers, unlike their European counterparts which to a greater extent operate internationally (Norges Bank, 2019a).

The sector consists of 26 commercial banks and 100 saving banks (Norges Bank, 2019a). Today, the main distinction between the two banking types is ownership structure, and not which services they offer. The saving banks are mainly small, but have formed extensive alliances, such as SpareBank1 Alliance consisting of 14 banks, and the Eika Group consisting of nearly 70 banks. These alliances started to form in the 1990s, with the aim of sharing services unrelated to the banking activity. This was necessary in order to be cost efficient and enabled them to compete with larger commercial banks, which are often full-service providers (Norges Bank, 2019a).

The number of bank branches has declined drastically over the last decades, and since the beginning of 1990, the number has more than halved to about 900 branches today (Finans Norge, 2017). Both the large commercial banks, and smaller saving banks, are cutting back on the number of branches and point to changes in consumer behavior and new technological developments as some of the main drivers of these changes (Fjelltveit & Aldridge, 2016; Frimand-Anda, 2017). Internet banking has changed the way customers interact with their banks and an increasing number of customers do not physically visit their bank (Jensen, 2015).

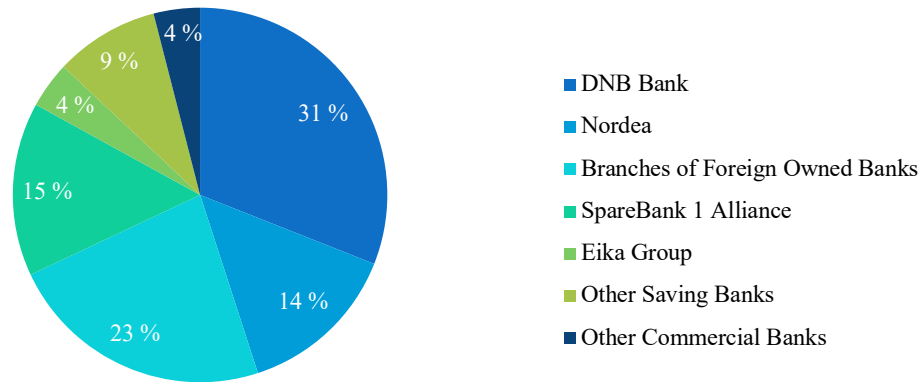


Figure 1 Market share of gross lending to the corporate market, December 2018 (Translated from Norges Bank, 2019a).

Despite the large number of banks in Norway, the concentration is relatively high with a few banks dominating the market, Figure 1 (Norges Bank, 2019a). DNB has the largest share of total gross lending to the corporate market with a 31 % market share. Overall, the market is dominated by Norwegian-owned banks. Though, after the deregulation of the banking sector in 1985, foreign-owned banks and branches are increasing their market shares. Today, branches of foreign owned banks and Nordea, which is a branch of the Swedish Nordea Bank AB, account for 37 % of gross lending to the corporate market in Norway. Other large foreign owned banks in the Norwegian market are Santander, Danske Bank and Handelsbanken (Lars-Tore Turtveit, 2017).

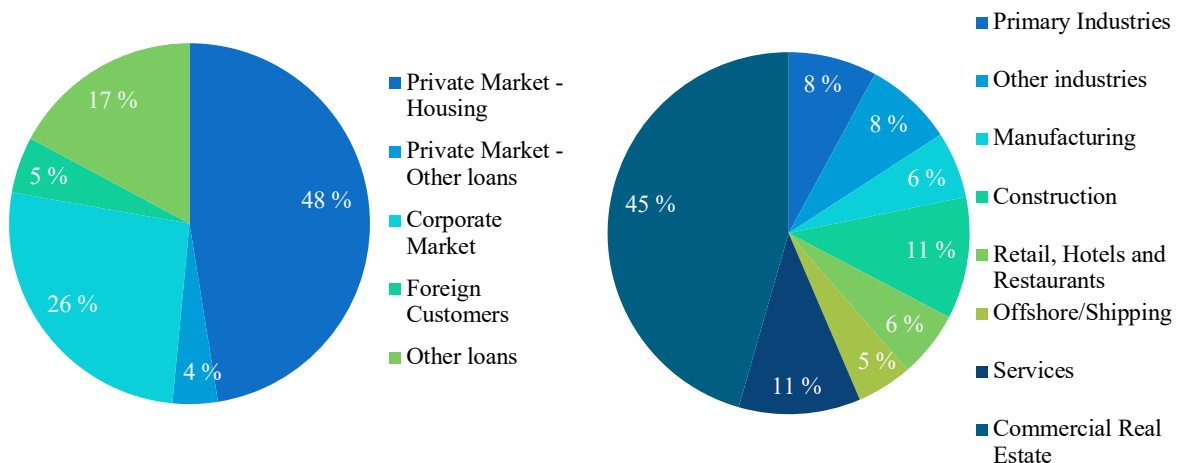


Figure 2 Total of lending in percentage from banks and mortgage companies in Norway, December 2018 (Translated from Norges Bank, 2019a).

Figure 3 Lending to the corporate market from banks and mortgage companies in Norway, December 2018. Other industries consist of natural resources, oil service, transportation and unallocated. Loans to foreign customers are not included (Translated from Norges Bank, 2019a).

Lending accounts for most of the assets of Norwegian banks and the largest loan share goes to private house mortgages and the corporate market, Figure 2 (Norges Bank, 2019a). In regard to lending to the corporate market, the variation between different industries are relatively small, Figure 3. However, commercial real estate stands out with a share of 45 % of total loan volume to the corporate market (Norges Bank, 2019a).

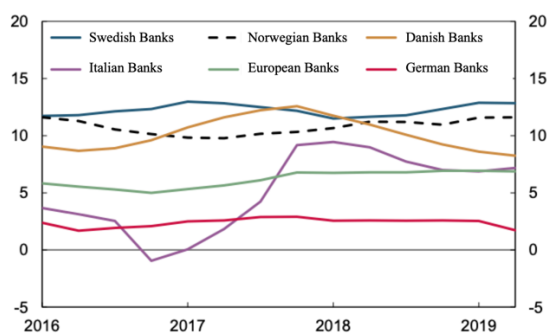


Figure 4 Return on equity after tax. Large Norwegian banks and European banks. Moving average over four quarters in percentage. Q1 2016 until Q2 2019 (Translated from Norges Bank, 2019c).

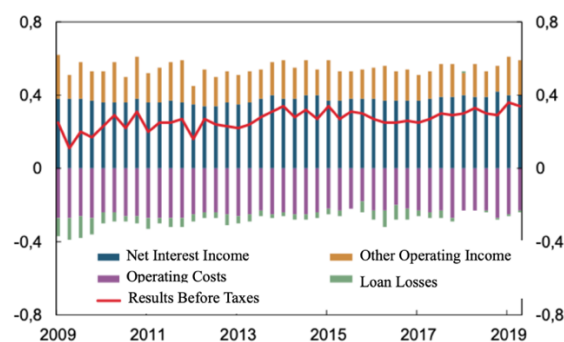


Figure 5 Decomposed earnings of large Norwegian banks, measured as percentage of average assets (Translated from Norges Bank, 2019c).

Over the last years, the large Norwegian banks have maintained their profitability and, together with Sweden, are at a high profitability level compared with other European banks (Norges Bank, 2019c), Figure 4. Low loan losses and stable net interest income are contributing factors to their profitability, Figure 5. Interest rates on loans have increased more than deposit rates and have thus increased net interest rates. According to Norges Bank (2019c), the profitability of Norwegian banks is expected to be maintained over the next few years. However, some important potential risks are increased losses and reduced margins due to increased competition between banks and newcomers.

2.2. Characteristics of Norwegian Firms

There were approximately 582 000 firms in Norway in the beginning of 2019, which represents an increase of 0.8 % from the preceding year (Statistics Norway, 2019b). The net growth in number of firms, i.e. the difference between new start-ups and closures, has been positive, but varying, over the last decade. About 30 % of new firms are still active after five years, with the highest survival rate in Sogn and Fjordane with 37.7 % and the lowest survival rate in Svalbard with 20 % (Statistics Norway, 2019b).

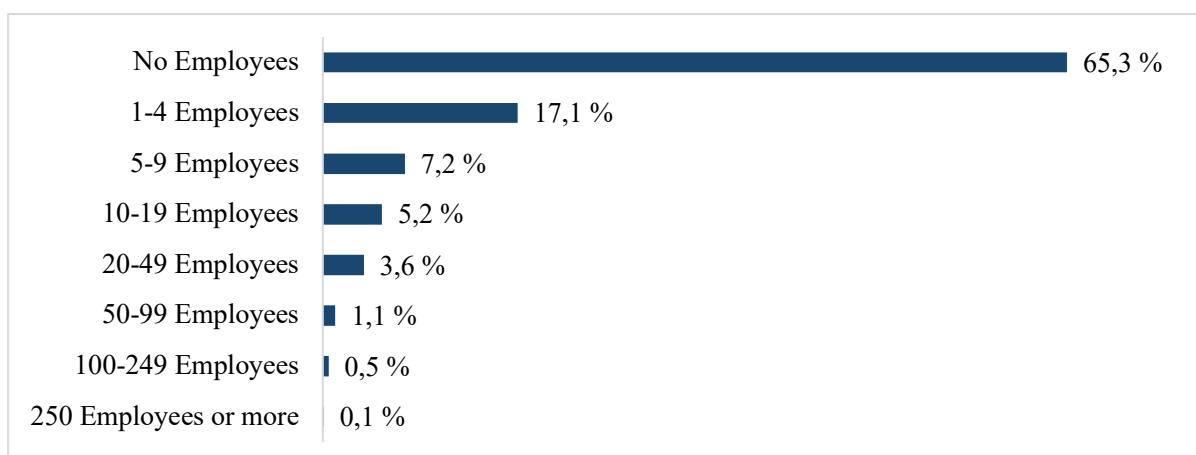


Figure 6 Distribution of firms in Norway by size (Statistics Norway, 2019b)

Small and medium-sized firms make up more than 99 % of all Norwegian businesses, and only 18 % of all firms have five employees or more, Figure 6 (Statistics Norway, 2019b). In addition, nearly two-thirds are without employees and only 0.1 % of all firms have more than 250 employees. The highest concentration of firms is in Oslo, where 15 % of all firms are located. Oslo is also the county with the greatest presence of large corporations, and more than 30 % of all firms exceeding 250 employees are situated in Oslo. The remaining counties have a relatively similar distribution of firms, where counties with large cities hold approximately 9 % of all firms, while counties with a lower population hold approximately 5 % of all firms. It is a notable goal for the Government to facilitate for businesses in all parts of the country, as businesses are important for vibrant communities, employment and value creation in rural areas (Regjeringen, 2019).

The largest proportion of the work force, 78 %, is employed in the service industry, where healthcare and retail are the industries which employ the largest number of people, 567 200 and 361 100 respectively (Statistics Norway, 2019c). In comparison, the oil and gas industry employ 51 600 people but their value creation in gross product, i.e. the value of what is produced minus the operating costs associated with producing it, is 606 billion NOK, more than twice as much as the retail sector.

Norway is a long and narrow country, with a very long coastline, which is traditionally divided into counties and municipalities (Thorsnæs, 2019a). Another method is to divide the Norwegian market into 46 different economic regions (Bhuller, 2009) (see Appendix 2 for a complete list of regions). The division into economic regions is based on the commuting distance between

the center municipality and the surrounding municipalities. This is done to reflect actual workforce-flow between the municipalities, in addition to trade-flow.

2.3. Financial Stability in the Norwegian Banking Sector

Because of their great societal significance, banks are subject to extensive regulation. A well-functioning banking system is critical in a modern economy in order to enable payments and transactions and as a mean of credit supply (Norges Bank, 2019a). The consequences of a malfunctioning banking system can easily become severe. The Norwegian banking crises from 1988 to 1993, and the Great Recession from 2007 to 2009, raised awareness of how instability in the financial markets can lead to deep national and international recessions (Grytten & Hunnes, 2016). For that reason, there is an ongoing effort, nationally as well as internationally, aimed at making institutions and markets, including the banking sector, more robust to economic shocks (Norges Bank, 2019a). Monitoring, laws and regulations and a healthy competitive environment are essential for an efficient and well-functioning banking system.

The Norwegian banking crisis, in the late 1980s and early 1990s, showed the importance and consequences of regulation and competition in the banking sector (Moe, Solheim, & Vale, 2004). Regulations on banks' credit supply and interest rate were lifted, and loans were generously subsidized through tax benefits. This led to a large credit expansion and resulted in asset bubbles, overheating of the economy and the most severe financial crisis since World War II (Grytten & Hunnes, 2016). During the preceding regulatory regime, banks had been exposed to little credit risk. In addition, the credit rationing induced banks to primarily select the best credit risk, as they could choose from a large pool of applicants with unsatisfied credit demand. After the regulations were lifted, in the mid 1980s, many banks started to broaden their lending and expanded into new geographical and business areas of which they had limited knowledge (Moe, Solheim, & Vale, 2004). The rapid growth in credit supply occurred in a banking environment characterized by fierce competition for market shares. One of the reasons banks struggled when the regulations were lifted, was that they did not have the time or competence to properly evaluate the candidates or lacked focus on risk management. This resulted in excessive operational and credit risk.

In addition to banks' own risk management being insufficient, public supervision was poor (Grytten & Hunnes, 2016). The Banking Inspectorate was reorganized as Finanstilsynet in 1986, in order to carry out a more coordinated and thorough supervision. However, the

restructuring phase was characterized by a period with hardly any supervision. Combined with the fixed exchange rate policy, i.e. a procyclical monetary policy in order to maintain the exchange rate, bad governance is said to be one of the main reasons for the banking crisis (Grytten & Hunnes, 2016).

Today, we have a well-functioning cooperation between Finanstilsynet, the Ministry of Finance and Norges Bank in Norway (Steigum & Thøgersen, 2013). The Ministry of Finance is responsible for promoting proposals for legislative amendments in the Parliament (*Stortinget*), Finanstilsynet is responsible for supervising the financial markets to ensure that rules and regulations are upheld (Norges Bank, 2019a), whereas Norges Bank is responsible for monitoring the payment systems and financial infrastructure, and contribute to emergency preparedness (Norges Bank, 2019b). In addition, the Norwegian Competition Authority (*Konkurransetilsynet*) supervise the competitive environment in the banking sector, with regards to competition between banks and how laws and regulations may affect the competitive environment (Konkurransetilsynet, 2019).

A robust banking sector, in combination with well-functioning monetary and fiscal policy, contributed to a relatively moderate financial crisis in Norway during the Great Recession from 2007 to 2009 (Grytten & Hunnes, 2016). Greater knowledge of risk management and improved banking legislation after the Norwegian Banking Crisis, is said to be some of the main reasons for the stability in the Norwegian banking sector today. However, Finanstilsynet's stress test from June this year, indicates that many banks may be strongly affected in the event of a serious setback in the Norwegian economy, and will not be able to meet the regulatory capital requirements at the end of the stressed period (Finanstilsynet, 2019). In the event of a deep recession, the vulnerability in the banking sector will mainly be due to increased loan losses, in particular on loans to non-financial firms.

3. Related Literature

3.1. Theoretical Literature

3.1.1. The Effect of Competition on Banks' Risk Taking

The economic theory on the effect of competition on banks' risk taking offers differing views, where two of the main directions in the literature are the *competition-fragility* view and the *competition-stability* view (Jiang, Levine, & Lin, 2017; Vives, 2016; Berger, Klapper, & Turk-Ariss, 2008; Marques-Ibanez, Leuvensteijn, Zhao, & Altunbas, 2019). The first view argues that competition leads to increased risk, while the latter view argues that competition leads to less risk.

The traditional *competition-fragility* view argues that competition leads to *greater* risk taking by banks (Berger, Klapper, & Turk-Ariss, 2017; Vives, 2016). According to this theory, competition diminishes market power and decreases profit margins, which in turn result in reduced franchise value that encourages banks to take on more risk. Franchise value represent intangible capital that will only be captured if the bank remains in business (Berger, Klapper, & Turk-Ariss, 2017). Banks with diminishing market power and lower profits, face lower opportunity costs of going bankrupt. To the contrary, a bank with more market power enjoys higher profits and has more to lose if it increases its risk exposure and fails. Hence, when a bank cares about the future, it will moderate its risk taking (Berger, Klapper, & Turk-Ariss, 2017).

Furthermore, this view argues that smaller profit margins will lower the incentives of banks to generate costly information to attract business from competitors (Jiang, Levine, & Lin, 2017; Marques-Ibanez, Leuvensteijn, Zhao, & Altunbas, 2019). In other words, competition could result in a value-deterioration of the information obtained by banks about their potential customers and a relative increase in the associated costs. Hence, banks operating in credit markets with high levels of competition, exhibit more careless screening and monitoring, eventually resulting in high levels of systemic risk

Under the alternative *competition-stability* view, competition in the banking sector might result in *reduced* risk taking by banks (Jiang, Levine, & Lin, 2017). Even though a rise of competition

might lower banks' profits, this also tends to reduce interest rates charged on loans (Berger, Klapper, & Turk-Ariss, 2017). In turn, lower interest rates may attract lower-risk borrowers by reducing adverse selection and risk shifting by reducing moral hazard. With increased funding costs, safer borrowers would be discouraged from lending, while higher risk borrowers are induced to choose riskier projects and are likely to face higher probability of default (Jiang, Levine, & Lin, 2017; Boyd & De Nicoló, 2005; Stiglitz & Weiss, 1981; Berger, Klapper & Turk-Ariss, 2008). Furthermore, competition can make banks more comparable and transparent, facilitating for better monitoring and reduced bank risk (Berger, Klapper, & Turk-Ariss, 2017).

Overall, this shows that the theory is not conclusive with regards to the effect of competition on banks' risk taking, and hence it is an empirical question.

3.1.2. The Relationship Between Physical Lending Distance and Risk

The theory on the relationship between physical lending distance and risk, mainly focus on small and medium sized firms (SME) as these firms often are opaquer than large firms (Liberti & Petersen, 2018). This is essential, as the theory in large is concentrated on the ability of a bank to obtain information about the borrowing firm and the ability to use that information to evaluate the risk associated with that firm. Related literature on the subject often make a distinction between two types of information, hard and soft (Liberti & Petersen, 2018). Hard information about a lender is quantitative, easy to store and transmit in impersonal ways, and includes information from financial statements, payment records, credit ratings etc. To the contrary, soft information is harder to quantify and requires a knowledge of its context to fully understand. A consequence is that physical distance plays an important role on the ability to collect soft information, since such information is, by definition, difficult and expensive to collect and transfer over long distances. Hence, the theory implies that physical proximity between the lending bank and the borrowing firm is necessary in order to collect such information.

The distinction is often made between relationship lending and transaction-based lending (Uchida, Udell, & Yamori, 2006). Relationship lending refers to banks basing their loan decisions on the collection of soft information over time, while transaction-based lending refers to all other lending processes, often based solely on hard information. Since small firms have less obligations regarding financial reporting, they are often described as opaquer.

Consequently, banks rely to a bigger extent on soft information and internal customer history when evaluating small firms, i.e. relationship lending. However, Berger & Udell (2006) argue that this is an oversimplification as select transaction-based lending techniques might be applied for more opaque firms. This entails that small firms do not only obtain financing through relationship lending but are subject to credit ratings and other types of more transaction-based lending. It might therefore be argued that the more dependent a bank is on soft information to obtain relevant information and properly evaluate the risk associated with a firm, the more important it will be with physical proximity.

Technological developments have resulted in a growth in the amount of numerical data available about borrowers, and more effective ways of combining soft and hard information (Vives, 2016). Nevertheless, different banks will have different proportions of relationship-based and transaction-based operations. Collectively, the theory implies that the available information and communication technologies, determine the limits of the area within which a bank can lend safely (Granja, Leuz, & Rajan, 2019).

3.1.3. The Theory of Risk Behavior over the Business Cycle

The theory of the financial-instability hypothesis (Minsky, 1982) emphasizes financial market fragility in the normal life cycle of an economy, and how financial relations in a capitalist economy leads to instability and eventually financial crises. Minsky's theory is one of the most recognized theories on financial crises and focus on key mechanisms in the economy that pushes it towards a crisis. The model is a Keynesian endogenous crisis model that emphasizes the loss of financial stability as a common denominator for all financial crises (Grytten & Hunnes, 2016). In the event of financial instability, the economy is often characterized by strong credit growth and increasing asset prices. The reason behind this credit growth can be on both the supply and the demand side.

Minsky (1982) distinguishes between three phases in the economy over the business cycle, which are categorized by different operational behavior by financial agents. In the early phase of the business cycle, the economy is characterized by hedge finance, where borrowers' ability to make debt payments is based on their current cash flows from investments (Grytten & Hunnes, 2016). Then, the economy evolves into speculative finance. During the shift to speculative finance, profits increase in the aggregate (Minsky, 1982). Hence, the ability to pay back debt is based on current cash flows and profits from increasing market prices. This leads

to increased credit and economic bubbles in the economy. Finally, the economy develops into Ponzi-finance. In this final phase, neither the current cash flows nor the growth in market prices are sufficient to meet future obligations. Therefore, one must rely on the expansion of capital, e.g. issuing shares or increased borrowing, in order to make debt payment. The two last phases of the business cycle are not sustainable and will result in a financial crisis.

Minsky (1982) stress how the financial-system behavior affects the business cycle and the different phases of operating in finance. The last two phases in the business cycle are often characterized by excessive optimism and credit expansion. Hence, agents in the economy often have excessively positive expectations for future returns and base their loan decisions on this. This behavior can be found both among lenders and borrowers. Furthermore, Minsky argues that our behavior pattern is strongly influenced by our recent experiences, hence our risk appetite will change throughout the business cycle (Grytten & Hunnes, 2016). The more time that passes since the economy was last characterized by Ponzi finance and recession, the greater the risk appetite of agents in the economy, i.e. both lenders and borrowers abandon caution in an economic upturn. Thus, there is an underlying pro-cyclical effect in the economy, relying on regulations and supervision by authorities to reduce the effects of such pro-cyclical behavior.

3.2. Empirical Literature

The main source of inspiration for our research was a recent study by Granja et al. (2019) on small business loans originated in the U.S. over the period 1996 to 2016. They find that competition induces banks to exacerbate risk taking in boom periods by using lending distance as a proxy for risk. Their findings show a long-run trend towards greater lending distances, in addition to a significant cyclical component to such distances. Furthermore, they find that a sharp departure from trend-distance, between the lending bank and the borrower, is indicative of increased risk taking. Finally, they find that such behavior occurs when banks are exposed to greater competitive pressure.

3.2.1. Cyclicalities of Credit Standards

A number of studies have empirically investigated the cyclicalities of credit standards. One example is a study by Lisowski, Minnis & Sutherland (2017), who used data from the construction industry in the U.S. They found that banks reduced their collection of financial statement verification in debt financing, i.e. exhibit more careless screening and monitoring, in

the years leading up to the financial crisis in 2008. This trend was reversed when economic growth became negative. Additionally, they found that banks that collected lower proportions of financial statements suffered higher losses, supporting that such behavior leads to worse bank performance in the event of a crisis.

Furthermore, Degryse, Matthews & Zhao (2018) and Presbitero, Udell & Zazzaro (2012) provide empirical evidence of a cyclical tendency in credit rationing. The former study investigates the sensitivity of banks' credit supply to SMEs in the UK before and during the financial crisis. They find that during the crises, SMEs that have banks within their territory, whose functional distance is close, i.e. the distance between the branch and the bank's headquarter, face greater credit supply. Thus, this implies that further functional distance leads to credit rationing. Presbitero et al. (2012) find similar effects when studying manufacturing firms in Italy, where banks are quicker at dropping their distant clients in a downturn.

3.2.2. Geographical Proximity and Lending Decisions

The relationship between geographical proximity and lending decisions has also inspired a large number of studies, mainly on small business loans. In Norway, a recent study on the corporate loan market shows that borrowers are significantly more likely to initiate a new banking relationship with a bank, after the travel distance to its branch is reduced (Herpfer, Mjøs, & Schmidt, 2018). They find that closer distance creates an economic surplus from lower transaction costs. Along the same lines, Brevoort & Hannan (2006), using data on small business lending in nine metropolitan areas in the U.S., found that distance operate as a deterrent to lending, especially for smaller banks, and that this effect grew stronger over time.

Furthermore, Agarwal & Hauswald (2010) study the effects of distance on the collection and use of private information in informationally opaque credit markets. They show that borrower proximity facilitates for the collection of soft information, which is reflected in the bank's internal credit assessment. Similarly, Mian (2006) suggests that greater distance decreases the incentives of a loan officer to collect soft information, in addition to making it more costly to produce and communicate soft information.

DeYoung, Glennon & Nigro (2008) also study the relationship between distance and information. They document that the use of hard information result in an increase in borrower-lender distance. In addition, they find evidence that loan performance declines with distance.

However, the impact of distance declined over time, suggesting that changes in the banking industry, e.g. developments in information and communication technology, during their sample period improved banks' ability to lend to small businesses.

This latter finding, that the impact of distance on loan performance declined over time, are supported by a study from Sweden. Here, Carling & Lundberg (2005) did not find any empirical evidence that verified the existence of geographical credit rationing on behalf of the bank in their sample. Nor did they find any evidence that information asymmetry increased with distance. They argue that these findings might be a result of technological changes which have improved the monitoring process, hence outweigh the need for geographical proximity.

Collectively, the empirical evidence suggests that proximity between the lending bank and the borrowing firm might affect the credit supply and screening abilities by banks. However, there are also empirical evidence indicating that technological advancements make this relationship less important.

3.2.3. Competition and Stability

Interest in the relationship between competition and stability in banking was triggered by the seminal article by Keeley (1990) (Berger, Klapper, & Turk-Ariss, 2017). In his article, Keeley (1990) investigated the reasons behind the large surge of bank failures in the beginning of the 1980s in the U.S. Until the 1950s and beginning of 1960s, banks were partially protected from competition by a variety of regulatory barriers. For example, laws which limited or prohibited branching and interstate bank expansion, and deposit rate regulations. Keeley's hypothesis was that changes to the degree of competition faced by banks in the subsequent years, may have reduced banks' incentives to act cautiously with regard to risk taking.

In his empirical findings, banks with more market power hold more capital relative to assets, i.e. have higher capital ratios (Keeley, 1990). He argues that higher capital ratios, holding asset risk constant, provide more protection against failure. Furthermore, he argues that higher capital ratios reduce shareholders incentive to take on risk, as higher capital ratios imply greater losses for equity holders in the event of default. In addition, he finds that banks with more market power have a lower default risk as reflected in lower risk premiums. This implies that banks with *less* market power, i.e. faced with more competition, have lower capital ratios, which may lead to more risk-taking, and higher default risk. Thus, he argues that at least some of the

increase in bank failures, may be due to a general decline in the banks franchise value associated with increased competition (Keeley, 1990).

To the contrary, the empirical finding of Boyd & De Nicoló (2005) indicate that the probability of failure increases with more concentration in banking, suggesting that competition helps to enhance financial stability. Boyd & De Nicoló (2005) argue that increased concentration in banking markets could encourage higher interest rates, which, in turn, heighten moral hazard concerns with bank borrowers. Similarly, Liu, Molyneux & Nguyen (2011) investigate the relationship between competition and bank risk-taking in Southeast Asian, and find that competition does not increase bank risk-taking.

Altogether, there is not a clear consensus in the empirical literature on whether competition enhances or diminishes financial stability.

4. Empirical strategy

We consider our study to be three-folded, as there are three questions which we need to investigate prior to answering our research question. The first question is whether there is cyclical variation in lending distance in Norway, i.e. are banks more willing to give out loans at greater distances in the midst of a boom. A faster-than-trend expansion of the average lending distance is either evidence of a rapid improvement of technology or suggestive of increased bank risk taking (Granja, Leuz, & Rajan, 2019). If the latter is true, more distant loans should be associated with higher risk, especially those made during a boom. We therefore move on to our second question which is whether distant lending is in fact riskier, implying that distance can be used as an adequate proxy for risk. If such a relationship is found, we will examine our final question. This question is whether competition among lenders exacerbates risk taking during a boom, using distance as a proxy for the risk associated with the corporate loan.

4.1. The Cyclical Variation of Lending Distance in Norway

First, we want to investigate whether there is cyclical variation in the distance between the closest branch of the lending bank and the borrowing firm in Norway. To the best of our knowledge, there are no previous studies on whether a cyclical pattern in lending distance is evident in the Norwegian corporate loan market.

This model only includes observations when there is created a *new* loan account a in bank i for firm j . Since we are interested in investigating how the business cycles affect the lending distances, it is only relevant to look at the loans initiated in time t for each state of the business cycle. Otherwise, we will not be able to estimate the relationship between the business cycle and lending distance. We do not account for any negotiation time, hence the year associated with the new loan represents the year the firm receives the loan. In addition, we are only interested in the first time a loan contract is set up, excluding cases where the loan amount increases. We assume that if a firm increases its liabilities because of a new project or initiative, it will be expressed as a new loan account and not as an increase in an existing account.

Our model allows us to measure the effect of business cycle fluctuations on distant lending, using unemployment rate as a proxy for the business cycles and our main variable of interest. The dependent variable is the geodetic distance in kilometers between the borrowing firm j and

the closest branch of the lending bank i at time t . This is under the assumption that the loan is provided by the closest branch of the lending bank, as we do not have access to data about which branch that provide each loan. Even though this is an assumption, it is in accordance with practice (Carling & Lundberg, 2005).

The geodetic distance represents the length of the shortest curve between the centroid of a borrower's postal code and the centroid of a lender's closest branch postal code (Granja, Leuz, & Rajan, 2019). An alternative to using the geodetic distance, is to use geographical distance by road or in travel time. However, that would raise questions as to the correct choice of road network system or travel mode (Carling & Lundberg, 2005). Like Carling & Lundberg (2005), we assume that the geodetic distance serves as a good approximation for the average distance between the borrowing firm and the lending bank. The geodetic distance is created by SNF and is based on information on banks' branch location from Finance Norway and firms' location information from SNF. We measure distance at *account* level, in order to exploit the whole dataset.

The model is a log-linear model, using a regression where we control for unobserved characteristics and use cluster-robust standard errors in all regressions.

We propose the following general model in order to analyze the cyclical variation in distant lending:

$$(1) \quad Distance_{ajit} = \alpha + \gamma_1 Z_{mjt} + \delta_{rjt} + \mu_t + \varepsilon_{jt}$$

where $Distance_{ajit}$ is our dependent variable which returns the logarithm of the geodetic distance in kilometers of account a between firm j and the closest branch of bank i in year t . For interpretation reasons, we construct the logarithm of the geodetic distance. This is because we believe that an increase in unemployment rate will have the same effect in percentage on short and longer lending distances. If we were to use non-logarithmic form, that would imply that a one percentage point increase in unemployment rate would have, on average, the same effect in absolute kilometers on short distances, e.g. below 10 km, and long distances, e.g. above 300 km. We assume that this is not the case, as a decrease of 5 km from 10 km to 5 km, creates a larger change and will likely be of greater importance, than a decrease from 300 km to 295 km.

Our main variable of interest, Z_{mjt} , is the unemployment rate in municipality m of firm j at time t . We control for regional effects, e.g. there are natural differences in distances between

different regions, by including δ_{rjt} for region r of firm j at time t . In addition, we control for the time effect, i.e. if there is a natural increase in lending distance over time, with μ_t .

4.2. The Relationship Between Distant Lending and Risk in Norway

Next, we wish to study whether increased lending distance is associated with increased risk in the Norwegian corporate loan market. Theory on relationship lending suggest that such a relationship might exist due to asymmetric information. Still, the empirical literature is somewhat ambiguous (DeYoung, Glennon, & Nigro, 2008; Agarwal & Hauswald, 2010; Carling & Lundberg, 2005) and gives grounds for further investigation with data from Norway.

Our model allows us to measure the relationship between lending distance and the risk associated with corporate loans in Norway, using distance as the main variable of interest and different risk measures as the dependent variable. The model is a linear-log model using restricted cubic splines on our explanatory variable, *Distance*, and run regressions using fixed effects and cluster-robust standard errors. A more detailed and theoretical explanation behind using fixed effects and cluster-robust standard errors can be found in Appendix 1.

The risk associated with a corporate loan can be measured in several different ways. However, we choose to include two well-established risk measures, the *Z-Score* and *Credit Rating*, in our analysis. The risk associated with a loan is the extent to which the company manages to repay the loan. The Altman Z-score (2000) is a widely used risk measure, which signals the likelihood of a company going bankrupt, which is one of the reasons a loan is not repaid. The Credit Rating indicates the financial health of a firm, where one of the main components are the company's payment history (Hjelseth & Raknerud, 2016). Credit ratings are widely used by banks and other investors in decision making, as they provide an independent certification of the firm's finances (Pereira, Laux, & Carvalho, 2014). Hence, these measures may reflect the risk associated with a loan.

We propose the following general model in order to measure the impact of distant lending on risk:

$$(2) \quad Risk_{jt} = \alpha + \gamma_1 RSC(Dist_{jit}) + \theta_{jt} + \lambda_j + \delta_{rjt} + \mu_t + \varepsilon_{jt}$$

where $Risk_{jt}$ is one of our dependent variables, *Z-Score* or *Credit Rating*, indicating the risk associated with firm j at time t . These measures reflect the risk associated with each loan,

instead of the aggregated risk associated with the entire loan portfolio of each bank. We want to investigate the relationship between risk and lending distance, where lending distance is calculated between borrowing firm and lending branch. As we do not have any risk measures on branch level, we choose to use risk measures on firm level instead of bank level. This allows us to exploit more of the variation in the data.

The explanatory variable $Dist_{jit}$ is the logarithm of the geodetic distance between the borrowing firm j and the closest branch of the lending bank i at time t . We assume that the estimated relationship between distance and risk may vary over the lending distance. For example, there might exist a threshold for when asymmetric information begins to play a role in lending decisions. Furthermore, after a certain lending distance, the impact of further increase might have a diminishing effect on risk. It is therefore beneficial to include a restricted cubic spline function, presented as $RCS(\cdot)$, which is used to transform the explanatory variable, $Distance$.

The values of the explanatory variable are split up into different segments, where the values that define the end of one segment, and the start of the next segment, is defined as knots (Croxford, 2016). Restricted cubic splines are used as a flexible way of modelling the relationship between the dependent and explanatory variable (Wu, 2009), e.g. the relationship between our two measures of risk and lending distance.

We choose the *restricted cubic* spline for our function. *Cubic* means that it allows our variable to be polynomial of third degree. This enables us to use more of the variation in our data. In addition, *restricted* means that the relationship is constrained to be linear before the first knot and after the last knot, which reduces the influence of outliers in our data (Wu, 2009).

The restricted cubic spline provides a way to formally test the assumption of a linear relationship between lending distance and risk (Croxford, 2016). However, if a non-linear relationship exists, the cubic splines allow it to be modelled well. Hence, it will reduce model misspecification and provide insight into the relationship between our dependent variable and main variable of interest. In addition, the restricted cubic spline is useful when analyzing skewed data, i.e. when the values of a variable does not seem to have a normal distribution (Sharma, 2019), which we believe may be the case of the data on lending distance.

Next, we have to decide the number and position of the knots. It has been found that the location of the knots in the restricted cubic spline model is not crucial in most situations and that the

model is more sensitive to the number of knots (Wu, 2009). Further, Stone (1986) illustrated that five knots are often enough to provide a good fit. However, if the sample size is large and there is reason to believe that the relationship between the dependent variable and the explanatory variable changes quickly, more than five knots can be used (Croxford, 2016). We believe this might be the case in our dataset, since our observations over distance are skewed, and as mentioned, the relationship between lending distance and risk might vary over distances. Hence, we choose to use six knots, which is placed on our 1st, 65th, 75th, 90th, 95th and 97th percentiles of distance, which is at approximately 0 km, 4.0 km, 7.9 km, 36.8 km, 111.2 km and 296.9 km. We believe that a continuous flexible function between these distances is appropriate in order to estimate the relationship between risk and lending distance. We choose not to place any knots between the 1st and 65th percentile, as we believe that it would not serve any economic purpose to divide the relationship between zero and 4 km even further. This is due to the fact that we believe banks will be able to assess the risk on a par with distances at 0 and 4 km.

Finally, we control for fixed effects for firm j in year t by including θ_{jt} , e.g. size and age, as we believe that loan conditions for large and mature firms will differ from that of small and newly established firms. Some industries are more capital intense than others and some industries experience industry specific fluctuations that do not correlate with the business cycle. However, by including firm fixed effect with the variable λ_j , this is accounted for as firms will remain in the same industry over the sample period. Regional effects, e.g. there are natural differences in distances between different regions, are controlled for by including δ_{rjt} for region r of firm j at time t . Finally, the time effect is controlled for with μ_t .

4.3. The Effect of Competition on Distant Lending over the Business Cycle

In our final model, we want to measure how competition in the corporate loan market in Norway affects banks' risk taking, through distant lending, over the business cycle. If we find greater cyclical variations in risk-taking, through lending distance, for banks exposed to more competition, this indicates that competition might have a negative effect on the stability of the banking sector. This will imply that banks exposed to more competition have an increased effective risk tolerance, through an increased willingness to make loans at greater distances. If we do not find that competition affects banks' risk taking, through distant lending over the

business cycle, this will imply that we do not find any evidence that competition leads to less stability in the banking sector in Norway. Theory suggests that competition might induce excessive risk-taking due to reduced franchise value and less incentives for costly screening and monitoring. However, competition might also lead to better lending conditions and safer borrowers. Thus, the effect of competition on banks risk-taking is uncertain.

We use a continuous-continuous interaction term between the competition measure and the business cycle indicator. With a continuous-continuous interaction term, it is possible to estimate how the effect of one continuous independent variable on the dependent variable changes as the values of a second continuous variable changes (Institute for Digital Research and Education, 2019). Thus, we are able to estimate whether increased degree of competition causes increased variation in lending distances over the business cycle fluctuations, i.e. whether competition has an impact on the relationship between the business cycle indicator and lending distance.

Our model is a log-linear model, using a difference-in-difference approach, where the dependent variable serves as a proxy for the risk associated with a corporate loan. We use the logarithm of distance, since we believe that an increase in competition will have the same effect in percentage on short and longer lending distances.

We propose the following general model in order to measure the impact of competition on distant lending over the business cycle:

$$(3) \quad Dist_{jit} = \alpha + \gamma_1 C_{sjrt} \times Z_{rt} + \theta_{jt} + \lambda_j + \mu_t + \varepsilon_{jt}$$

where $Dist_{jit}$ is our dependent variable, constructed as the logarithm of the geodetic distance between the borrowing firm j and the closest branch of the lending bank i at time t . The interaction term between our competitive measure C_{jrt} and the business cycle indicator Z_{mjt} , serves as the main variable of interest and allows us to measure the impact of competition in different states of the cycle, on the risk taking by banks. The competitive measure, C_{sjrt} , is based on the competitive environment in the banking sector and is both the HHI of region r of firm j at time t and the HHI of sector s in region r of firm j at time t . The cycle indicator, Z_{mjt} , is the unemployment rate in municipality m of firm j at time t . If increased competition leads to instability, through excessive risk taking, i.e. increased lending distances, in the midst of a boom, it would be reflected as a positive coefficient of the interaction term. This will reflect

that banks that experience higher degrees of competition has a more procyclical pattern in their lending distances, than banks exposed to less competition.

Like in the previous model, we control for fixed effects for firm j in year t by including θ_{jt} , e.g. size and age, because we believe that loan conditions for large and mature firms will differ from that of small and newly established firms. Some industries are more capital intense than others and some industries experience industry specific fluctuations that do not correlate with the business cycle. However, by including firm fixed effect with the variable λ_j , this is accounted for as firms will remain in the same industry over the sample period. Finally, the time effect is controlled for with μ_t .

5. Data

5.1. Data Sources and Treatment of Data

In this study, we exploit several datasets that, when combined, offer a unique combination of information covering the population of Norwegian firms and banks in the period 1997-2013. Our final dataset includes loan specific information for every loan account associated with corporate customers during the sample period. Together with locational information of borrowing firms and bank branches, and accounting information on all corporate firms and banks throughout the period, we are able to investigate whether competition in the Norwegian corporate loan market leads to excessive risk taking and less stability in banking.

Our main advantage in this study lies in our ability to study the full population of corporate loans provided by banks in Norway for more than 15 years. This enables us to control for unobserved effects, which otherwise could have caused endogeneity in our model. Furthermore, accounting data and loan specific information are based on official registers, which is audited by authorized auditors and tax authorities, and are therefore of high quality. Together with firm specific information and location information, we are able to obtain a unique dataset.

The first dataset is provided by the Norwegian Tax Authorities (*Skatteetaten*). It offers unique data covering the population of Norwegian banks and detailed information on all loans with its associated interest payment made in the corporate sector in the period 1997 to 2013. Furthermore, it provides information that enable us to identify both the borrowing firm and the lending bank of each loan account throughout the period. The dataset yields insight into just above 15 million observations in the corporate sector, with 4.5 million unique accounts divided by nearly 800 000 customers.

Next, we acquire extensive firm-specific information through a rich database assembled by the Institute for Research in Economics and Business Administration (*SNF*). The database contains information about the firms, and includes location, industry codes, detailed audited accounting data, age and more, for the period 1993 to 2014. Additionally, the SNF database contains individual firms' credit rating, generated by Bisnode, a company which delivers analytic services. Consequently, we are able to connect loan information from the tax authorities to firm specific information for all corporate loans in Norway from 1997 to 2013.

Further, information on banks' branch location is provided by Finance Norway (*Finans Norge*) in their annual bank location register (*Bankplassregisteret*). Together with the SNF database, we are able to generate the lending distance between firms and banks, under the assumption that the loan is provided by the closest branch of the lending bank, measured by the geodetic distance. Combined, these datasets enable us to connect firm-specific information about corporate customers to their bank-borrower relationships, with respective lending distances.

Comprehensive accounting information on Norwegian banks and other financial institutions are gathered by Finanstilsynet in the ORBOF-database, in a collaboration between Finanstilsynet, Norges Bank and Statistics Norway. We have access to this dataset through SNF, and it contains, among other things, non-performing loans and loss-provision rates of each bank in each year of our sample period. However, these measures are provided for each legal unit and not on branch level. Since we wish to investigate whether increased lending distance is associated with increased risk, we assume that these aggregated measures will remove some of the variation in the dataset and not reflect the increased risk associated with increased lending distance. We believe this is especially true for large banks such as DNB, where the risk associated with increased lending distances of selected loans are unlikely to be reflected in e.g. increased loss-provision rates of the entire bank. Hence, we choose to not use these measures as the risk measures in our analysis.

Finally, Norwegian Centre for Research Data (NSD) provides a wide range of statistics on municipality level, such as unemployment numbers and demography numbers. These statistics are used to reflect the geographical variation in the business cycle fluctuations and entail that we can measure the business cycle for the municipality of each firm. We choose to measure business cycles at the firm level, and not branch-level, since we believe that the lending branch will assess the risk of the loan based on the conditions of the firm. In most cases, we assume that the lending bank and the borrowing firm will be located in the same municipality, as most lending distances are short. Whenever lending distances are longer, we believe that the lending bank is interested in the state of the business cycle that the borrowing firm is experiencing, as this might reflect the risk associated with a loan to a greater extent. Note that all data are reported based on the municipality classification of 2013.

In our research we depend on several variables from each dataset mentioned above. However, earlier research conducted by scholars and professors at the Norwegian School of Economics (NHH), enable us to use a partially processed dataset where some variables are already merged

into the main dataset provided by Skatteetaten. These variables are the number of employees, Bisnode's credit rating, industry classification and founding year. The remaining variables are merged by us.

Cleaning of the Data

In our initial cleaning, we omit all observations of accounts without a loan and those with negative loans, since our research target the corporate loan market, other observations are omitted. Next, we find that some observations belong to firms that have gone bankrupt. If a firm go bankrupt in year t but have observations in subsequent years, we omit observations after year t . Finally, we omit all observations with negative assets.

The purpose of our analysis is to measure the effect of competition on risk taking through the variation in distant lending over the business cycle. We therefore require information about both distances between firms and branches, and geographical variation in the business cycle fluctuations. The branch location and geodetic distance from the firm's location to the closest branch from the inside bank are obtained from SNF's dataset. All observations with missing locational information are omitted.

In order to merge with statistics from NSD, such as unemployment, we need information on municipality numbers in our main dataset. The dataset from NSD uses municipality classification of 2013, hence we need to update the municipality numbers in our main dataset to this classification. We do this by using postal codes as the key identifier. Whenever the postal code has changed during our sample period, information about municipality numbers are missing. Hence, we identify the updated postal codes and the corresponding municipality numbers, on 2013 classification, from a public registry. We then manually match the correct municipality number with the original postal code in our dataset. As postal codes are required in order to match observations with locational information from Finance Norway (*Bankpllassregisteret*), which is reported yearly, we do not change the postal codes in our dataset.

Subsequently, we merge the dataset with data from NSD containing information about unemployment and population in all municipalities. Then we merge economic regions based on Bhuller's (2009) classification of economic regions in Norway, with municipality numbers as the key identifier. The classification is based on the commuting distance between the center

municipality and the surrounding municipalities. The economic regions are later used when constructing competitive measures and when controlling for regional differences. We choose to omit observations in region 12, Oslo, because the region is abnormal with regards to unemployment rate, number of firms, presence of bank branches and so forth. Since a large number of banks are present in Oslo, we believe that all the firms in this region will have very short lending distances. In addition, the competitive measure will indicate very low concentration in the banking sector. We assume that this will affect our estimates, as a large share of observations are in the Oslo region, and hence our results will be biased. Observations in Svalbard are also omitted, as we lack data on unemployment and the geodetic distance will either be zero or extremely large in this region.

The dataset from SNF contains two different industry classifications, one from 2002 and one from 2007 set by Statistics Norway, which corresponds with the industry classification NACE set by the European Union (Statistics Norway, 2008). However, these classifications are not consistent throughout the sample period. We therefore decide to use the industry codes that are consistent in both classifications. This results in nine industry codes, in addition to “Other Services”. Observations that are not consistent in the two classifications, or lack sufficient industry information, are placed in the category “Other Services” to avoid losing observations. Whenever a firm lacks the industry code in one or several years, we assign the firm with the industry code from year $t-1$ or $t+1$, in cases where industry codes are reported in those years. The industry classification used in the dataset is presented below. The financial sector (9) is omitted as their lending structure and terms often deviate from other firms, and hence are not relevant to our analysis.

(1) Agriculture, (2) Offshore and Shipping, (3) Transportation, (4) Manufacturing, (5) Telecom, IT and Tech, (6) Electricity, (7) Construction, (8) Wholesale and Retail, (9) Finance and (10) Other Services.

Finally, we omit all firms that are not corporate firms. Our study wishes to measure whether competition leads to more risk taking and distant lending in the Norwegian corporate loan market. Therefore, entities such as foundations (STI), Norwegian Registered Foreign Businesses (NUF) and Housing Cooperations (BRL) are omitted.

5.2. Constructed variables

5.2.1. Dependent Variables

In order to measure the effect competition has on risk taking, through the variation in distant lending over the business cycle, we first have to establish two things. Whether there is cyclical variation in lending distances in Norway and whether the risk associated with a loan, increases with the lending distance. If this is established in our findings, we will continue with analyzing the impact of competition on distant lending over the business cycle.

We choose to include three different dependent variables. The first dependent variable is *Distance*, which shows the variation in lending distances in Norway, both gradually over time and over the business cycle fluctuations. The other two dependent variables relate to the risk associated with a loan, Altman's *Z-Score* and Bisnode's *Credit Rating*, where the credit rating will be used as a robustness test.

Distance

The first dependent variable, *Distance*, is constructed in order to measure the effect of distance on banks risk taking over the business cycle. When we construct the logarithm of the geodetic distance, some adjustments are necessary in order to keep the observations with a geodetic distance equal 0, approximately 166 000 observations. These observations will be lost when converted to logarithmic form. Hence, we choose to transform the distance variable by taking the logarithm of $(1 + \text{distance})$.

Z-Score

The first risk-variable, the Altman Z-score, is a widely used risk measure in empirical studies and is a measure of a company's likelihood of bankruptcy, calculated by using yearly firm-specific information (Altman, 2000). The original Z-score was constructed in 1968 as a measure of the probability of bankruptcy for publicly traded companies in the U.S. Altman (2000) later constructed a revised Z-score which is also suited for private firms, both manufacturers and non-manufacturers, including non-U.S. companies. In our analysis, we use the revised Z-score as it has a wider usage, e.g. it is suited for both small and large companies, in contrast to the original Z-score. We therefore assume that it is appropriate to use this Z-score on our sample

in Norway. The revised Z-score is a measure of the financial health and probability of bankruptcy, hence the risk associated with offering a loan to a firm. A higher Z-score indicates lower risk and lower probability of bankruptcy and a lower Z-score indicates higher risk and higher probability of bankruptcy.

The Z-score for firm j at time t is defined as:

$$Zscore_{jt} = 6.56 * \frac{Workcap_{jt}}{Assets_{jt}} + 3.26 * \frac{RetainedEarnings_{jt}}{Assets_{jt}} + 6.72 * ROA_{jt} + 1.05 * \frac{Equity_{jt}}{Assets_{jt}}$$

We construct the Z-score by using yearly firm-specific accounting information provided by SNF. *Workcap* is defined as the difference between current assets and current liabilities. *RetainedEarnings* is defined as all value added to equity that is reported in the income statement and not paid in dividends. Return on Assets (*ROA*) is defined as the percentage of profit a company earns in relation to its overall resources. It is constructed as net income divided by total assets. *Equity* is defined as the book value of equity. When constructing the Z-score, our sample includes some extreme values. We therefore omit observations outside the 1st and 99th percentile.

Credit Rating

The other risk-variable, Credit Rating, is based on a credit rating provided by Bisnode, for the years 2005 to 2013. Even though we lack observations for the first years of our sample, this variable is used in a robustness test. Hence, we allow that only observations from this period, is included when using Credit Rating as our dependent variable.

Bisnode determines a firm's credit rating based on assessments of four different areas: basic facts, ownership information, financial figures and payment history (Hjelseth & Raknerud, 2016). The credit rating is an evaluation of the risk associated with a prospective debtor and serves as a measure of the risk associated with a loan to firm j from bank i in our analysis.

Credit Rating is an ordinal variable with five values ranging from AAA to C, where a AAA corresponds to the value of 5 in our dataset and a C corresponds to the value of 1. In cases where a firm goes bankrupt or is liquidated, it is originally given the value 9 by Bisnode. We choose to replace these observations with the value 1, which reflects the poorest rating, so that the order of the ranking will be valid. In our analysis we care about the increased risk associated with a lower rating, and vice versa, hence the order is essential.

5.2.2. Explanatory Variables

In order to measure the effect competition has on risk taking through the variation in distant lending over the business cycle, we have to construct explanatory variables for business cycles and competition. In addition, in the model where we measure the relationship between risk and lending distance, we use *Distance*, which is presented under Dependent Variables, as an explanatory variable.

Unemployment Rate

First, it is necessary to choose a business cycle indicator for the sample period, for the purpose of measuring how risk taking through distant lending is affected by competition over the business cycle. Unemployment is one of the most recognized lagging indicators for the business cycle (The Conference Board, 2001). In addition, NBER's algorithm, produced by Leamer (2008), uses unemployment rate as one out of three indicators to define a recession. In Norway, Norges Bank and Statistics Norway use both GDP and unemployment rate to estimate the business cycle fluctuations (Aastveit, Jore, & Ravazzolo, 2015; Statistics Norway, 2019d).

In our analysis, we are interested in measuring the *geographical* variation in the business cycle, in order to utilize the variations within Norway in year t . Consequently, we choose unemployment rate at municipality level as a proxy for the business cycle. Unemployment- and population numbers at municipality level are provided by the Norwegian Center for Research Data (NSD). Even though GDP is a well-recognized measure of the business cycle, we choose to not use this measure as it is only available at aggregated levels.

Unemployment rate is usually constructed as

$$Unemployment\ rate = \frac{Absolute\ unemployment}{Workforce}$$

where *workforce* is defined as the sum of people unemployed and people employed. However, we only have access to unemployment and population numbers, and not employment numbers, on municipality level from NSD. The population numbers are made up of all men and women between the age of 16 and 66. We therefore use population on municipality level instead of workforce as the denominator when constructing the unemployment rate. Statistics on disability benefits from Statistics Norway (2019a) indicate that there is variation, in terms of the share of

the population in the workforce, between different regions in Norway². However, since we do not have access to data on employment from NSD, we assume that our unemployment rate, using population numbers between 16 and 66 as the denominator, is an appropriate proxy for the business cycle.

Furthermore, as the data is provided on municipality level, we choose to not alter this by aggregating to regional levels. As the division into economic regions reflects actual workforce-flow between municipalities (Bhuller, 2009), it could be useful to aggregate the unemployment rate to each economic region. However, we would lose variation in our data and therefore choose to not do this.

For interpretation reasons, we choose to multiply the unemployment rate by 100 in order to present the variable in percentage points. Our unemployment rate in municipality m of firm j at time t is defined as:

$$Unemployment_{mjt} = \frac{Absolute\ unemployment_{mjt}}{Population_{mjt}} \times 100$$

HHI – The Hirschman-Herfindahl Index

Next, we need a competitive measure in order to analyze competition in the banking sector. We choose to construct the Hirschman-Herfindahl Index (HHI) as our proxy for competition in our analysis. HHI is a widely used measure of concentration (Vives, 2016) and is also as a standard by the European Commission when measuring concentration levels (European Union, 2004). The overall concentration level in a market may provide useful information about the competitive situation in the market and is used in other empirical studies as a measure of competition (Canta, Nilsen, & Ulsaker, 2018) We choose the HHI as our competition measure as it is easily accessible and gives an indication of the competitive environment in the market. In a market with higher level of concentration, one assumes that a few large banks could promote collusive behavior, and be associated with higher prices, than in markets with many agents (Liu, Molyneux, & Nguyen, 2011). For this reason, the level of competition might depend on the number and size of existing banks, i.e. concentration level. However, other

² People receiving disability benefits are considered to be outside the workforce because they are unable to obtain income from work (Statistics Norway, 2019a).

factors, such as entry barriers, might be important in order to determine the competitiveness of a market (Vives, 2016). Such factors are not accounted for in the HHI, implying that HHI has its shortcomings as a competition measure.

We construct the HHI for both economic regions and industries within economic regions:

Economic Region – Share of loans per bank i at time t in each region r

$$x_{itr} = \frac{\text{total loans}_{itr}}{\text{total loans}_{tr}}$$

Industry – Share of loans per bank i at time t in each region r and industry y

$$x_{itry} = \frac{\text{total loans}_{itry}}{\text{total loans}_{try}}$$

The HHI – region and HHI – industry of bank i at time t can be written as:

$$HHI - region_{tr} = \frac{\sum_{i=1}^N x_{itr}^2}{1000}$$

$$HHI - industry_{try} = \frac{\sum_{i=1}^N x_{itry}^2}{1000}$$

The variable is constructed using data retrieved from the Norwegian Tax Administration and the SNF database and is calculated by summing the squares of the individual market shares of all banks in the market. We calculate the concentration in each of the 46 economic regions, as well as the concentration in each of the industries in these regions. We choose to measure concentration within economic regions, as we believe each region represents a local market. This is because economic regions reflect trade-flows within different areas (Bhuller, 2009).

The HHI ranges from 0 to 10 000, since the market share is measured in percentage and gives proportionately greater weight to the market shares of the larger firms (European Union, 2004). 10 000 indicate a monopoly situation and 0 indicate a perfect competitive market. HHI of more than 2 500 represents a highly concentrated market (Corporate Finance Institute, 2019). For interpretation reasons, we divide the score by 1 000. Otherwise a one-unit change in HHI will translate into a very small change in distance, i.e. the estimated coefficient will be very small.

5.2.3. Control Variables

To control for firm-specific variation, we construct a set of control variables. This includes measures of firms' age and size. In addition, we control for firms' industrial classification and economic region.

The loan terms of a firm will vary depending on which phase of the lifecycle it is in and the size of the firm. First, we create a dummy to illustrate if a firm is young or mature. Only 30 % of new firms still operate five years after establishment (Statistics Norway, 2019b). Young firms are therefore defined as five years or younger, while the remaining firms are categorized as mature.

Small firms are often informationally more opaque than large firms (Presbitero, Udell, & Zazzaro, 2012) and we therefore assume that larger firms are less sensitive to distant lending when negotiating a loan contract. Consequently, we control for the size of each firm and create variables based on the number of employees and the size of total assets.

First, we create dummies for small, medium and large firms, which is determined by the number of employees. This classification is used in order to split the sample in regressions, and descriptive statistics, in order to control for the effect when dealing with small firms. We assume that small firms are opaquer, and we want to investigate the variation between small, medium sized and large firms in our dataset. In addition, we use these classifications to control for firm size in our regressions. Note that a firm can go from one category to another throughout the sample period. The dummies are based on Statistics Norway's (Statistics Norway, 2019b) classification of firms by size group. Firm j at time t is defined as small if the number of employees is less than 10, medium if the number of employees is between 10 and 49 and large if the number of employees is 50 or more.

Large firms with revenue above a juridical limit are required to be audited (Altinn, 2019) and are therefore likely to give more detailed and reliable accounting information when negotiating a loan contract. We assume that the size of a firm's total assets is a good indicator for its size, hence we construct the logarithm of a firm's total assets.

Size for each firm j at time t is defined as:

$$Size_{jt} = \ln (TotalAssets_{jt})$$

5.3. Summary Statistics

After the cleaning of our dataset and construction of our variables, we are left with the following distribution of our most relevant variables:

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

Variables:	Observations	Mean	Median	St.dev	Min	Max
Z-Score	946 211	1.873	1.613	2.005	-3.809	8.100
Credit Rating	773 595	3.078	3.000	1.149	0.000	5.000
Distance	1 309 348	27.217	1.614	111.878	0.000	1 668
lnDistance	1 309 348	1.435	0.961	1.540	0.000	7.420
Unemployment	1 309 348	2.189	2.096	0.832	0.000	10.585
HHI _{region}	1 309 348	2.539	2.309	0.925	0.990	5.913
HHI _{sector}	1 309 211	2.851	2.583	1.194	1.105	10.000
Size _{lnAssets}	1 292 600	8.633	8.490	1.785	0.000	20.333
<i>Credit Rating ratios:</i>						
Rating: AAA	65 272	1.000	1.000	0.000	1.000	1.000
Rating: AA	252 836	1.000	1.000	0.000	1.000	1.000
Rating: A	212 476	1.000	1.000	0.000	1.000	1.000
Rating: B	177 357	1.000	1.000	0.000	1.000	1.000
Rating: C	51 350	1.000	1.000	0.000	1.000	1.000
N	1 309 348					

Due to lacking accounting information and industry classifications for selected firms, there are some variations in the number of observations for different variables. In addition, as previously mentioned, the Credit Rating by Bisnode is only available after 2005.

6. Descriptive Statistics

6.1. Sample Characteristics

Our sample consists of approximately 136 000 firms with about 1.3 million observations over the sample period from 1997 to 2013. The bulk of our observations are small and medium sized firms, which is consistent with the general characteristics of the Norwegian corporate market. Figure 7 shows the distribution of observations by firm size, where the classification is based on number of employees. As shown in Appendix 2, most firms are in the economic regions which house the largest cities in Norway, and Vestfold, Stavanger, Bergen and Trondheim stand out as the regions with the most firms. Generally, there is large variation in the number of registered firms between regions, where Bergen has the largest number of firms with 5 510 and Harstad has the smallest number of firms with only 89.

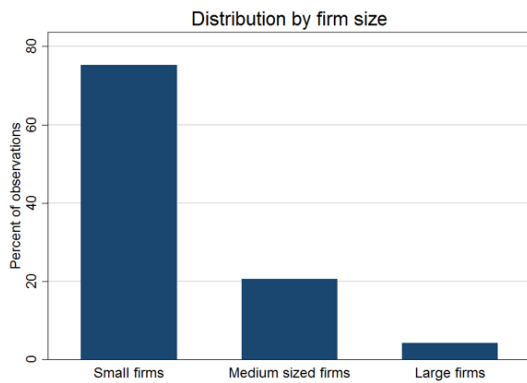


Figure 7 Distribution of observations by firm size

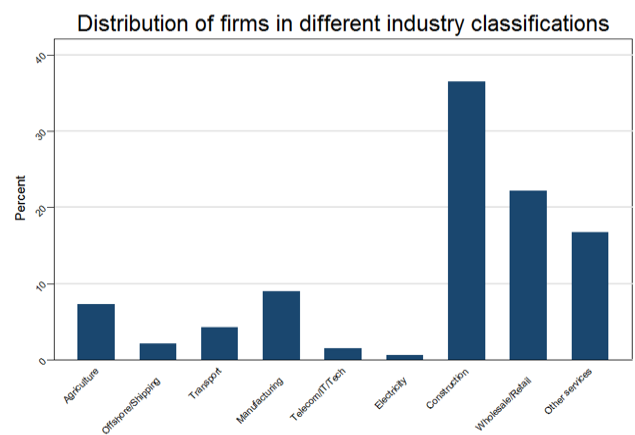


Figure 8 Distribution of observations by industry classification

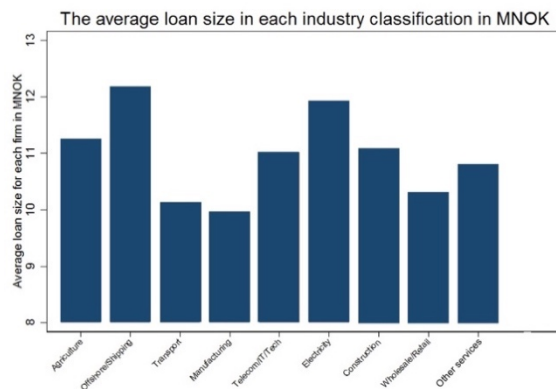


Figure 9 Average loan size by industry classification, in MNOK

Like the distribution of firm size, there are large variation in the distribution of firms between different industry classifications, shown in Figure 8. Most of our observations are in the industries Construction and Wholesale/Retail, while there are fewest observations in Offshore/Shipping, Telecom/IT/Tech and Electricity. However, the distribution varies between regions. For example, inland regions tend to have fewer firms in the offshore and shipping industry, in contrast to more western regions. Furthermore, there are for example large differences between regions in terms of observations in the agriculture industry, as this industry to a greater extent is dependent on geography and nature-related conditions.

Figure 9 shows the average loan size in different industry classifications. The variation is relatively small. However, Offshore/Shipping and Electricity stand out as the industries with the highest average loan size and also have the lowest number of observations. This makes sense as these industries are commonly characterized as capital-intensive. It is likely that firms in these industries, in addition to other large public traded firms, will receive additional funding from other sources than the corporate loan market. This might be the reason why we observe relatively small variation in average loan size between industries, even though the firms might be very different in terms of capital-intensity.

When studying the regions in Appendix 2, we observe that there are large variations on average yearly loan volume per firm between regions. Nordvest-Telemark has the lowest yearly loan volume per firm with only 3 million, while Bodø has the largest with close to 26 million. There may be several factors contributing to this result. First, it could relate to the proportion of firms which are capital-intensive. We believe this might be the case in Bodø, where we observe multiple large loans of which many are to electricity firms. Similarly, in Tromsø, there are several large loans to firms dealing in commercial real estate. Furthermore, there are some regions with large average loan volumes per firm. This may be a result of fewer companies in the region, where some individual companies have very large loans, thus raising the average for the region as a whole. We believe this might be the case in for example Nordmøre, where one company has more than seven billion in loans.

In regard to total loan volume, there are large variations between regions, where some regions stand out in terms of both large loan volumes and numerous firms. This applies to the Stavanger, Bergen, Trondheim and Bodø regions, which have a substantially higher total loan volume than the other regions.

Z-Score Variation

The average Z-score between different industries varies from 1.4 in the Electricity industry to nearly 2.5 in the Wholesale/Retail industry, Figure 10. Parts of this variation may be a consequence of some industries being more capital-intensive, which will give rise to the key figures in which the Z-score is based on. In the sample as a whole, the mean of the Z-score is 1.87 with a standard deviation of 2.01, hence the observed variation between industries are relatively small.

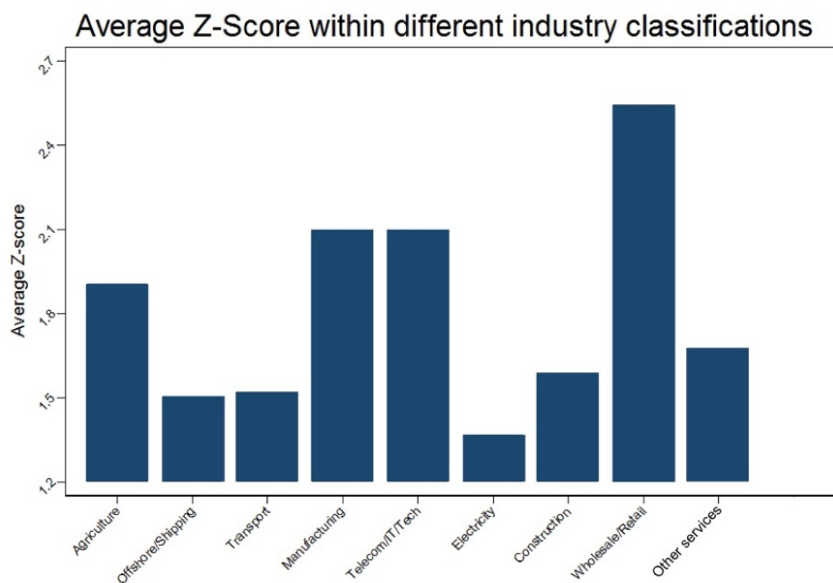


Figure 10 Average Z-Score by industry classifications

Competition Measured by HHI

There is large variation between different regions in regard to competition, measured as concentration by the HHI, Appendix 2. Sandefjord is the least concentrated region with a score of 1 531, whereas Bodø is the most concentrated region with a score of 4 609. One classification defines a highly concentrated market as a market with an HHI of 2 500 or more (Corporate Finance Institute, 2019). Based on this classification, 60 % of our regions are highly concentrated, which indicates that the banking sector in Norway is moderately competitive.

Unemployment

There is visible variation in average unemployment between different regions, Appendix 2. Vadsø has the highest average unemployment throughout the sample period of 3.6 %, while Valdres and Hallingdal have the lowest unemployment rate of 1.1 % and 1.2 % respectively.

As previously mentioned in the construction of variables, these figures are based on absolute unemployment figures where the whole population in the age group 16 to 66 is used as the denominator, instead of the workforce. This means that if there is variation in the number of people receiving disability benefits between regions, this will not show up in our numbers. This is also the reason why the unemployment figures are so low.

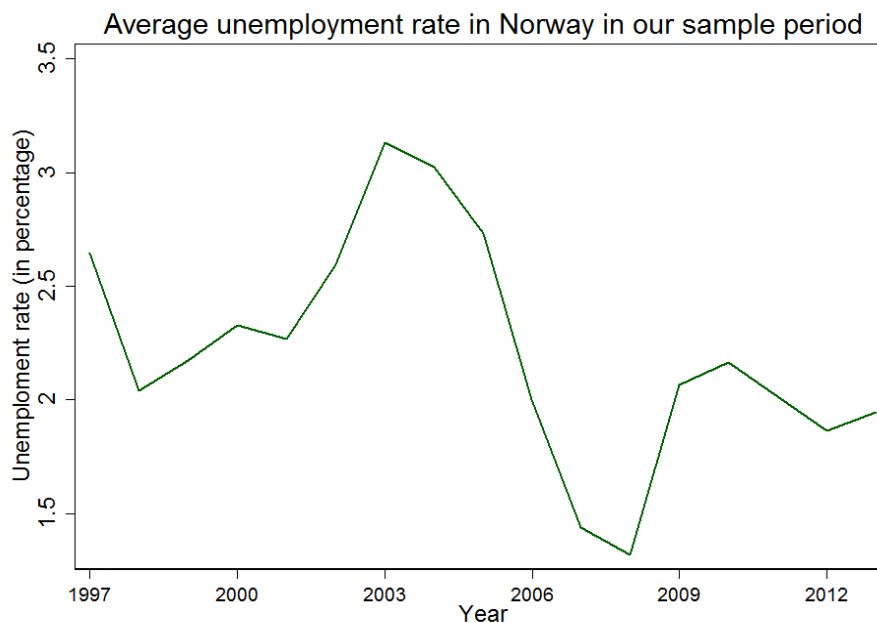


Figure 11 Average unemployment rate in Norway from 1997 to 2013

Figure 11 shows that the average unemployment figures for the entire sample follow cyclical fluctuations, with the largest decline in unemployment from 2003 to 2008. This coincides with the largest economic upturn in Norway in the period 1997 to 2013, as illustrated in Appendix 3, which supports that the unemployment figures can be used as a proxy for the business cycle.

6.2. Distance Characteristics

All of our models are based on lending distance. The characteristics of the relationship between distance and other variables in the corporate loan market in Norway is therefore important. As our main variable of interest, it is essential to understand how distance between the closest branch of the lending bank and the borrowing firm is distributed in our sample.

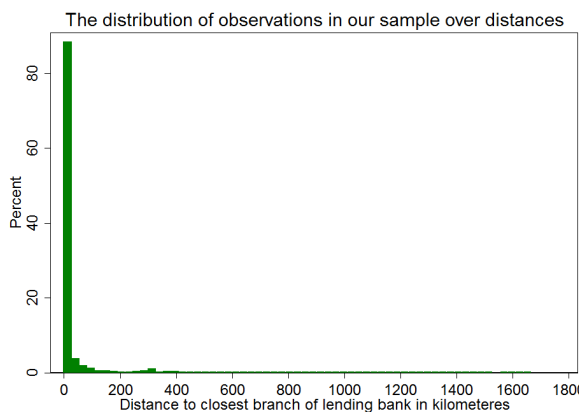


Figure 12 Distribution of observations over distances

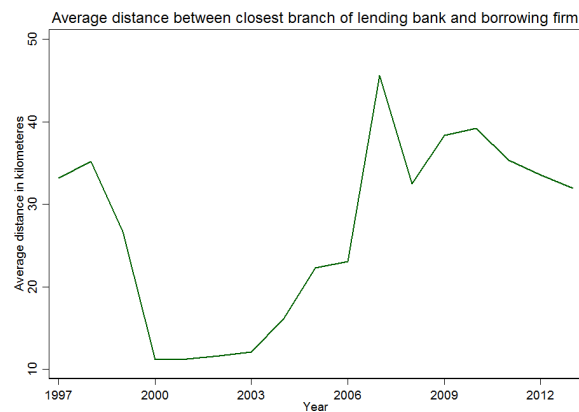


Figure 13 Average lending distance over the sample period

Figure 12 shows how our observations are distributed over the lending distances. The most important notion is that most of our observations are at a very short distances, with 50 % of all observations within 1.6 km and 90 % within 37 km. Technological changes have made it possible to communicate and transfer information easily over longer distances, which could suggest that relationship lending is of less importance in the corporate loan market today. However, these statistics might indicate otherwise.

The longest distances are just above 1600 km, and these extreme values can be decisive for the variation in average distances in different regions. Northernmost regions have the longest distances and these observations are mainly associated with foreign registered banks with a head office in Oslo and without affiliated branches in Norway. This applies, for example, to Santander Consumer Bank (*Santander*) and YA-bank, which have a large proportion of loans to car dealerships around the country, of which numerous loans have distances above 1 000 km. When comparing Santander to the rest of the sample, the 50th percentile are at distances of about 300 km, compared to 1.6 km for the whole dataset.

Overall, average distances are furthest in the northernmost regions, where Mid-Troms and Alta have the longest average distances. There are relatively small variations in average distance in the southern part of Norway and up to Nordmøre. Though, from Kristiansund and further north, we observe larger variations and longer distances.

Looking at the variation in average distance over the sample period, Figure 13, we observe that average distance is decreasing until year 2000 and gradually increasing from 2003 to 2007, before it decreases again. This may appear to be cyclical variation, as these fluctuations are consistent with the business cycles in Norway, as illustrated in Appendix 3. If this is the case, it might be suggestive of procyclical lending behavior, where banks take on more risk, in the form of increased lending distance, in boom.

However, other factors such as technological advancements, bank branch closures and an increase in Norwegian-registered foreign-owned banks during the sample period, might also have had an impact. For example, loans from Santander and YA-bank are only present after 2004. It is reasonable to assume that lending practices based on a head office in Oslo, without affiliated branches in other regions, coincide with technological advancements, since these loans are mainly online. We believe this is one of the reasons for the steep increase after 2005 in lending distances.

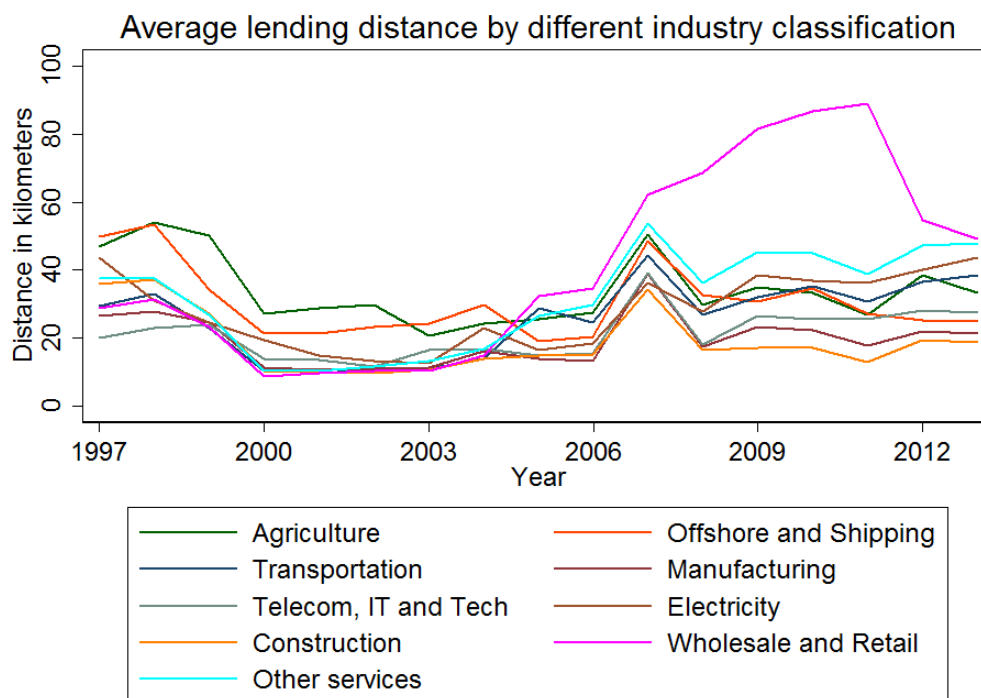


Figure 14 Average lending distance by industry classification

Next, we look at the average distance between different industries over the sample period, Figure 14. The average distances are relatively similar between industries up until 2007, which is the peak of the business cycle. In 2008, the average lending distance drops to approximately 2006 levels. The only exception is Wholesale/Retail, which separates from the others in 2007. This appears to be due to extreme values in this industry, as the distances for this industry at the 50th and 75th percentiles of distance are lower than for sample as a whole, but at the 90th percentile, distances are larger for this sector. The majority of the extreme loan distances in northern Norway are in this sector.

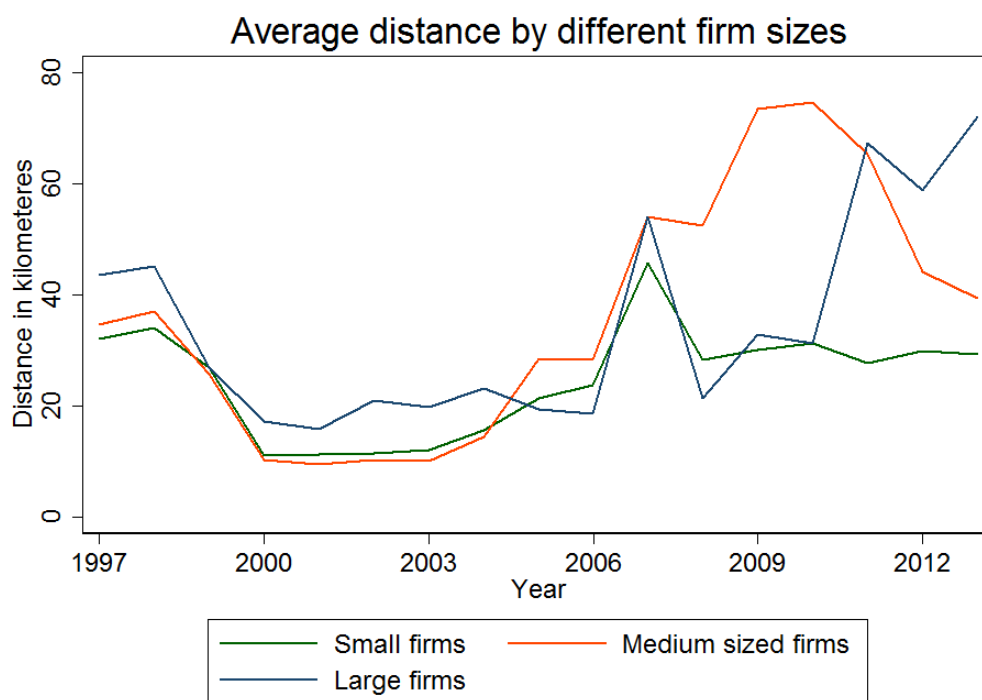


Figure 15 Average distance by different firm sizes

In regards to the average distance between different firm sizes, Figure 15, we observe that average lending distance for small, medium sized and large firms are relatively similar until 2007. After this, medium-sized firms' development coincides with the Wholesale/Retail industry. Many of the same observations are in both classifications, where a large proportion of the companies in the automotive industry are also classified as medium size.

The relatively small variation between average lending distance for different firm sizes may partly be a consequence of how the distance variable is constructed. It is likely that large firms, with large loans in particular, will address the headquarters to receive funding instead of the closest branch. If this is the case, our assumption when constructing the distance variable that

it is the closest branch of the lending bank that provides the loan, might be wrong. Hence, the calculated distances of large firms might not reflect the actual lending distance.

Furthermore, we observe that there is a significant increase in distance for large companies after 2010. Large companies in the period from 2010 onwards make up 3.9 % of all observations. The low share could cause some extreme values to easily raise the average. Within the 50th percentile of distance, there are no differences in average distances between firm sizes, but for the remaining observations of large companies, the average distance is greater.

7. Results

7.1. The Cyclical Effect on Lending Distance

In the first part of our analysis, we want to investigate whether there is a cyclical variation in lending distances. The business cycle fluctuations are measured by using unemployment rate at municipality level, where the variable is presented in percentage points. Hence, an increase of one unit in unemployment, equals an increase of one percentage point in unemployment rate in the municipality of each firm. If there is cyclical variation in distant lending, i.e. the lending distance increase more than trend in a boom and the opposite in a bust, we should see that unemployment is negatively and significantly correlated with distance.

We use the logarithm of distance as our dependent variable in this analysis. As mentioned in the empirical strategy, we only include observations of new loans and are therefore not interested in loan observations in subsequent years. Since we assume that small and opaque firms are more sensitive to cyclical fluctuations, we choose to run an additional regression where we only include small firms.

Table 2: *Log-linear model, using a regression where we control for unobserved characteristics where the logarithm of lending distance is the dependent variable*

Variables	(1) lnDistance	(2) lnDistance _{Small}
Unemployment	-0.0341** (-3.14)	-0.0208 (-1.94)
Time	0.0213*** (12.46)	0.0175*** (9.79)
Constant	1.556*** (24.33)	2.351*** (7.59)
Observations	504 425	350 386
Number of firms	128 231	106 023
Regional Effects	YES	YES

Note: The dependent variable represents the geodetic distance between the closest branch of bank i and the borrowing firm j in year t . The explanatory variable is the unemployment rate, which presents the average unemployment rate in municipality m of firm j in year t and is provided in percentage points. The time variable is a trend variable, which is included to control for how lending distance evolves throughout the sample period. The variable is presented as integers starting at 1 in the first year of the period and increase with 1 for each year. We control for regional effects by including dummies for each region. Column 1 presents the results for new loans in the whole sample and column 2 presents the results for new loans for small firms. T statistics is presented in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For the entire sample of new loan observations, presented in column 1, we find that an increase in unemployment rate is associated with a reduction in lending distance. This is consistent with theory on financial crises, given that distance can be used as a proxy for risk. A one unit increase in the unemployment rate, i.e. an increase of one percentage point, will on average be associated with a 3.41 % reduction in lending distance. The effect is significant at a 1 % level. In addition, we find that average lending distances throughout the sample period increase by 2.13 % annually, which is significant at a 0.1 % level. This implies that there is a cyclical effect, which is also greater than trend, in the sample period.

In column 2, we only include small firms in our regression, i.e. firms with less than 10 employees. In this regression, we do not find a significant relationship between unemployment and lending distance. However, the coefficient indicates that there is a negative relationship between the two variables, and that the magnitude of the cyclical effect may be smaller than we observe in column 1, which represent the whole sample.

Observations within the 98th percentile of Distance

As presented in descriptive statistics, a large share of the observations is within relatively short distances, while the variation in lending distance outside the 98th percentile of distance is very large. As previously mentioned, we believe there may be other reasons for these distances being long, such as the large proportion of loans to the automotive industry. Hence, we believe it is relevant to analyze the effect of unemployment on lending distances within the 98th percentile. If the long distances are due to other conditions, e.g. specific trade agreements, but are expressed as cyclical variation, it is necessary to investigate whether we observe the same effect within the 98th percentile, which represents the part of the sample that is of the greatest practical importance. The 98th percentile of distance includes most of our observations and express much of the variation in the dataset, but excludes distances above 320 km.

Table 3: Log-linear model using a regression where we control for unobserved characteristics where the logarithm of lending distance is the dependent variable. Observations within the 98th percentile of lending distance.

	(1)	(2)
Variables	lnDistance	lnDistance _{Small}
Unemployment	0.0143 (1.67)	0.0160 (1.70)
Time	0.0170*** (12.36)	0.0163*** (9.72)
Constant	1.222*** (23.34)	1.734*** (13.31)
Observations	489 719	342 267
Number of firms	126 944	104 916
Regional Effects	YES	YES

Note: The dependent variable represents the geodetic distance between the closest branch of bank i and the borrowing firm j in year t . The explanatory variable is the unemployment rate, which presents the average unemployment rate in municipality m of firm j in year t and is provided in percentage points. The time variable is a trend variable, which is included to control for how lending distance evolves throughout the sample period. The variable is presented as integers starting at 1 in the first year of the period and increase with 1 for each year. We control for regional effects by including dummies for each region. Column 1 presents the results for new loans in the sample within 98th percentile of distance and column 2 presents the results for new loans for small firms within the 98th percentile of distance. T statistics is presented in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In this regression, we find that the effect is almost the same in column 1 and column 2 in Table 3, i.e. for all observations within the 98th percentile and when only including small firms within the 98th percentile. In both regressions, the effect of unemployment on distance is only significant at a 10 % level, and contrary to the results in Table 2, it appears that increased unemployment has a positive effect on lending distances. This is not consistent with what would be expected according to economic theory, and might suggest that something unobserved in the regression for the entire sample, Table 2, may have led to a significant negative relationship.

As we still have large variation in lending distances in this regression, we choose to measure the effect of unemployment on distances within the 95th percentile of distance, to see whether the results are equally ambiguous. By only including distances within the 95th percentile, hence distances below 111.2 km, we find that an increase in unemployment rate of one percentage point, i.e. a one unit increase in unemployment, on average leads to an 2.24 % increase in lending distance. This effect is significant at a 0.1 % level. We get relatively similar results when only including small firms within the 95th percentile of distance, where a one percentage point increase in unemployment rate on average leads to an increase in lending distances of

2.56 %. This effect is also significant at a 0.1 % level. These results are somewhat consistent with our findings at the 98th percentile of distance and support that there may be a positive relationship between unemployment rate and lending distance. However, the relationship is significant, in contrast to our findings in Table 3.

Our results in the three regression; the whole sample, within the 98th percentile and the 95th percentile of lending distance, are not consistent. Hence, based on our analysis, we cannot conclude that there is a pro-cyclical variation in lending distances in Norway.

7.2. The Relationship Between Distant Lending and Risk Taking in Norway

The next step in our analysis is to establish whether distant lending in boom is, on average, riskier and hence amounts to additional risk taking by banks. If distant loans carry additional risk, in the form of less effective screening and monitoring, more distant loans should be associated with higher probability of default, especially those made during a boom.

First, we use Altman's Z-score, which indicates the likelihood of bankruptcy (Altman, 2000), as the main dependent variable. In order to test the robustness of this analysis, we then execute the regression by using Credit Rating, retrieved from Bisnode, as the dependent variable. We only have credit ratings after 2004, and there is less variation in this variable, hence it is appropriate to use in a robustness test.

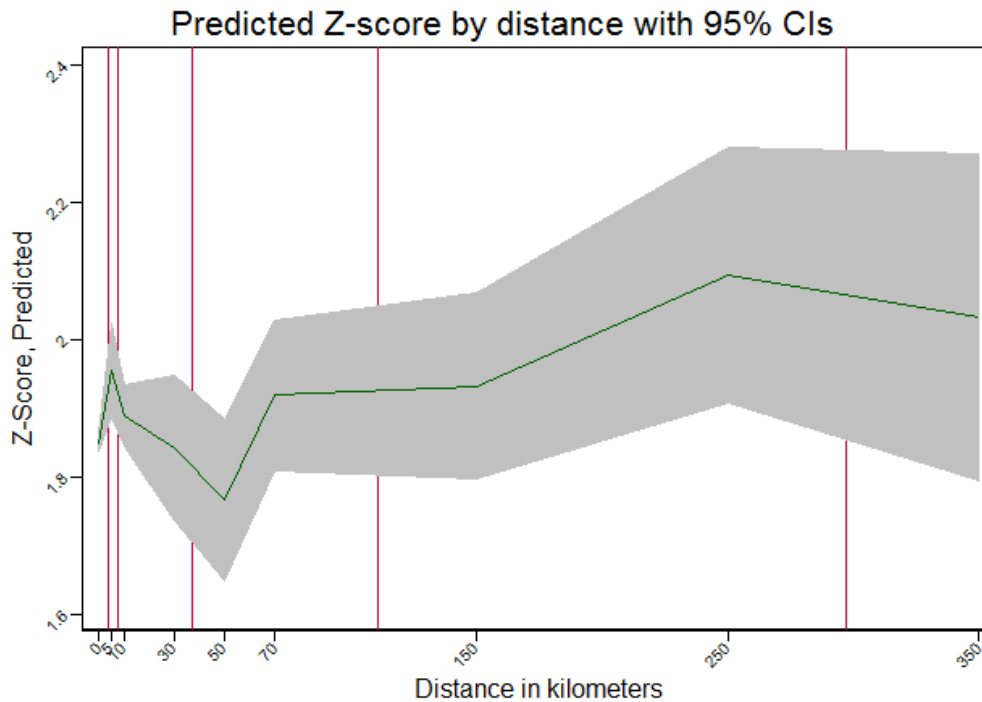
When using restricted cubic splines in our regression, we cannot interpret the magnitude of the coefficients and whether they are significant from a regression statistics table. We therefore have to illustrate the relationship between the Z-score and distance graphically, with the corresponding confidence intervals. However, the predicted Z-score, using restricted cubic splines on our explanatory variable, cannot be illustrated by a non-integer variable such as distance. Consequently, we have categorized the distances in different intervals, where our flexible model is illustrated by linear functions between each of the distance categories. This is shown in Figure 16, Figure 17 and Figure 19, which illustrate regressions where restricted cubic splines are used. However, in the regressions where we use the restricted cubic spline, the outcome with regards to distance is a smooth line, not with the kinks as observed. This is done to ease the construction of the figure. The regression line would be continuous between the knots, which are marked with red lines in the following figures. The knots are placed at the

percentiles at P65, P75, P90, P95 and P97, at distances of 4.0 km, 7.9 km, 36.8 km, 111.2 km and 296.9 km respectively.

7.2.1. Using Firms' Z-Score as a Proxy for Risk

Figure 16 Predicted Z-score by distance using the whole sample, with 95% CIs.

(The percentiles (and knots) at P65, P75, P90, P95 and P97 are marked with red lines)



The predicted Z-score illustrates the relationship between the risk associated with a loan and the lending distance between the borrowing firm and the closest branch of the lending bank. A higher Z-score is associated with lower risk and a lower Z-score is associated with higher risk. If increased distance is associated with increased risk, this would be reflected in Figure 16 as a falling graph.

In the first 5 km it appears that increased distance is associated with increased Z-score, though this variation is within a relatively small range on the Z-score. However, an increase on the Z-score by almost 0.1 unit, within a 5 km increase in distance, may be argued to be of economic importance. This correlation shows the opposite of what we would expect based on economic theory. Further, we observe that the Z-score falls with 0.2 units until 50 km, which includes more than 90 % of our observations. This means that for a large proportion of our observations, increased distance is related to increased risk. On the other hand, this is a relatively small

reduction over a larger distance interval, with a reduction of 0.2 units in the Z-score, which has a standard deviation of 2.01 in the sample. Therefore, we cannot conclude that there is a clear relationship between increased distances and reduced Z-scores, i.e. increased risk. Beyond this point, the predicted Z-score increases again, with a diminishing slope. Thus, the magnitude of distance on Z-score lessens as the distance increases. Still, this increase is so small compared to the increase in number of kilometers, that we cannot argue that we find a clear connection here either.

In order to interpret this plot causally, we use the confidence interval to evaluate how significant our estimations are. The confidence interval for the mean is a function of the sampling uncertainty of the estimates obtained in the regressions (Wooldridge, 2013), given that the observations have a normal distribution. With a large degree of freedom, as in our sample, the confidence interval is constructed as:

$$\hat{y} \pm (1.96 \cdot se(\hat{y}))$$

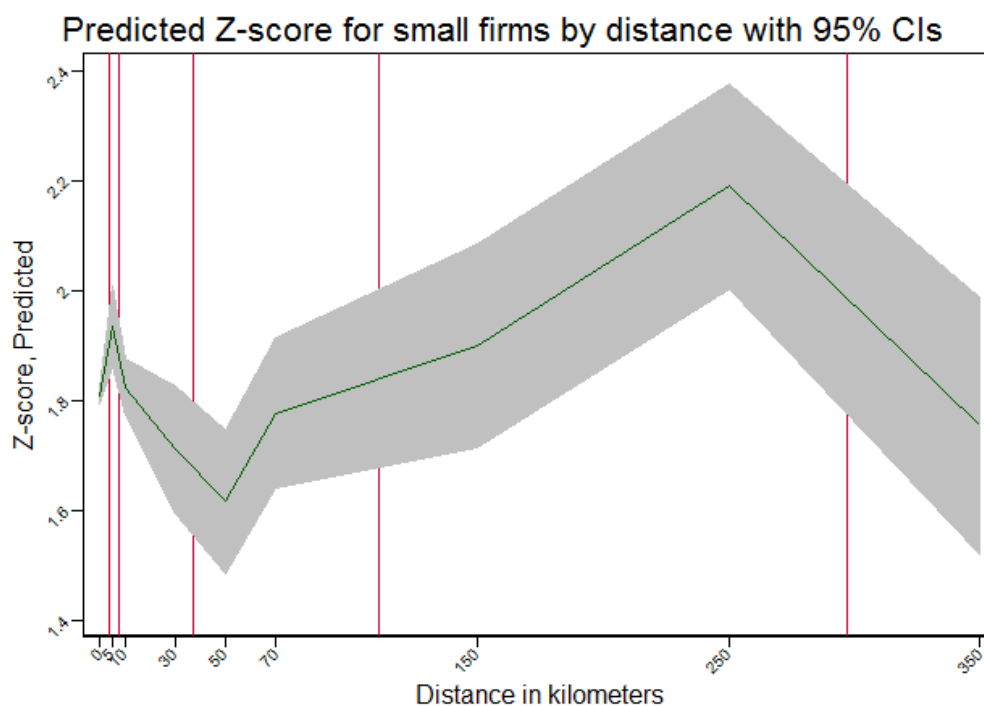
where \hat{y} is the predicted Z-score and $se(\hat{y})$ is the standard error of the predicted Z-score. We obtain the confidence intervals in Figure 16, Figure 17, Figure 18 and Figure 19 by using the *margins-plot* command in STATA. If the relationship between Z-score and lending distance is significant, the confidence interval should be relatively small compared to the magnitude of the standard deviation of the Z-score in our sample.

In our plot, the 95 % confidence interval is relatively small, as the confidence interval is approximately 0.2 units and the standard deviation of the Z-score is 2.01 in the sample. Consequently, the relationship is significantly positive within 5 km, i.e. increased lending distance is associated with reduced risk, then significantly negative between 5 and 50 km and finally significantly positive after 50 km. In addition, the confidence interval varies over the lending distances and is smaller for shorter distances. However, 75 % of the sample is within 8 km, which amounts to almost one million observations in our dataset. Solely relying on confidence intervals in such large samples can lead to causal interpretations of the results which are of no practical significance (Lin, Lucas, & Shmueli, 2013). Since we observe that the confidence intervals increase when there are fewer observations, we believe this may be the case at short distances. However, with such a small confidence interval overall, we believe that the relationship is significant.

Even though we observe a significant relationship between Z-score and lending distance, this relationship switches from being positive to negative and then positive again over the lending distances and the magnitude on the Z-score is relatively small. Hence, we do not find that increased lending distance is of economic importance with regards to the risk associated with a loan in our analysis.

Figure 17 Predicted Z-score by distance only including small firms, defined as less than 10 employees, with 95% CIs.

(The percentiles (and knots) at P65, P75, P90, P95 and P97 are marked with red lines)



Empirical studies show that small firms are often more informationally opaque than large firms, hence more challenging to evaluate when negotiating a loan contract (Presbitero, Udell, & Zazzaro, 2012). If these assumptions are correct, i.e. there is greater risk associated with small firms, it is necessary to control for this part of the sample.

Figure 17 presents the relationship between lending distance and risk when we only include small firms. There seems to be larger variation in the trend, but mainly on distances outside the 95th percentile of distance. It can be argued that observations within the 95th percentile are the part of the sample of economic importance. Similar to Figure 16, we observe increased Z-score within the first 5 km, before the Z-score drops until 50 km. The magnitude on the Z-score seems to be somewhat larger than for the entire sample. However, the magnitude in proportion to the

relatively large distance between 5 km and 50 km, may be argued to be relatively small. A reduction of 0.35 on the predicted Z-score over 45 km, may be of relatively little economic importance, considering the variation of the Z-score in the sample, with a standard deviation of 2.01.

After 50 km, there seems to be a negative relationship between risk and distance. We find it hard to argue why there should be a negative relationship. If such a relationship exists, it would imply that it is more difficult to monitor the firms with shorter lending distances. These findings are not consistent with the predictions of economic theory, which suggest that there is a positive relationship. This may indicate that there is something unobserved, which leads to less risk associated with increased lending distance and might be suggestive of endogeneity in our model.

Similar to Figure 16, the confidence interval is relatively small, which indicates that the relationship between lending distance and risk is significant. However, with a relatively small magnitude of the estimated relationship we cannot conclude that we find that lending distance is of economic importance for the risk associated with loans provided to small firms in our sample.

Cyclical Tendencies of Distance and Risk Taking

In the U.S., Granja et al. (2019) find that the relationship between distance and the likelihood of charge-off becomes positive and statically significant during the boom. Still, this relation becomes less pronounced, and eventually insignificant, in the ensuing downturn. This means that the relationship between risk and distance was mainly observable in the boom. We therefore choose to look at the years 2004 to 2007, which is the most prominent economic upturn in Norway in our sample period, see Appendix 3. Our results from this period shows similar effects as in Figure 16 and Figure 17. Hence, we cannot conclude that there are cyclical tendencies in the relationship between lending distance and risk in Norway.

The relationship between risk and lending distance within 90th percentile

A large proportion of our sample is located within short distances, where 90 % of our observations have a lending distance of less than 37 km between the borrowing firm and the closest branch of the lending bank. As previously mentioned, this part of the sample is of most practical importance. Consequently, we further investigate the relationship in this sample.

We do not use restricted cubic splines in this regression. However, in order to illustrate the relationship graphically, with confidence intervals, it is necessary to categorize the lending distances. *Margins-plot* cannot be illustrated by non-integer values as our distance variable. Consequently, the line has kinks and is not a smooth line like the line from our regression.

Figure 18 Predicted Z-score by distance within P90, with 95 % CIs.

(The percentiles at P65 and P75 are marked with red lines)

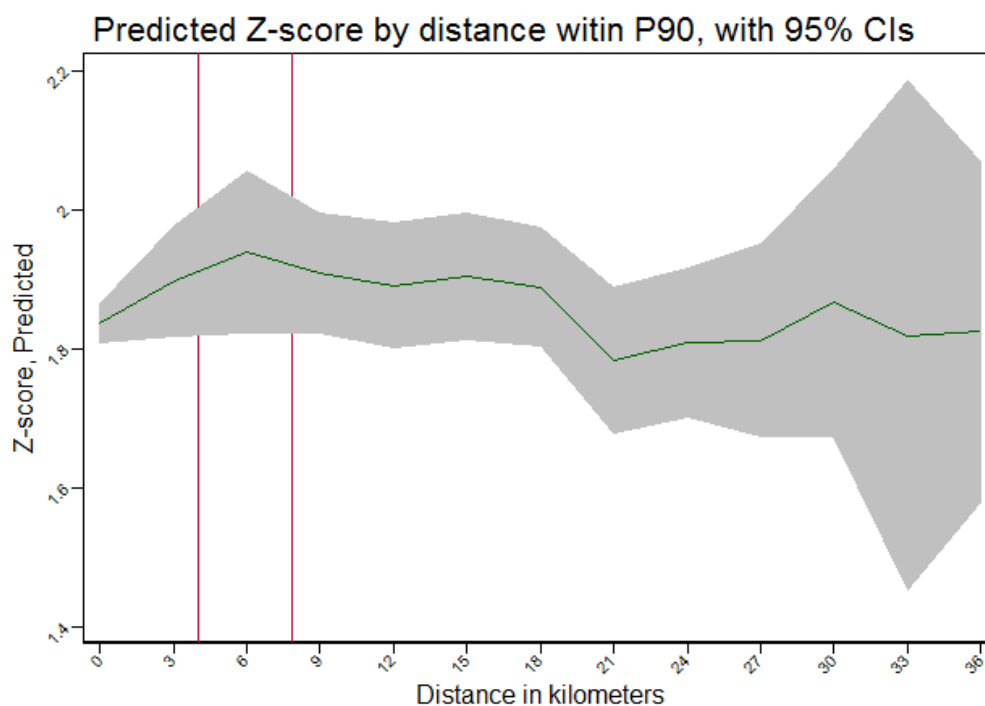
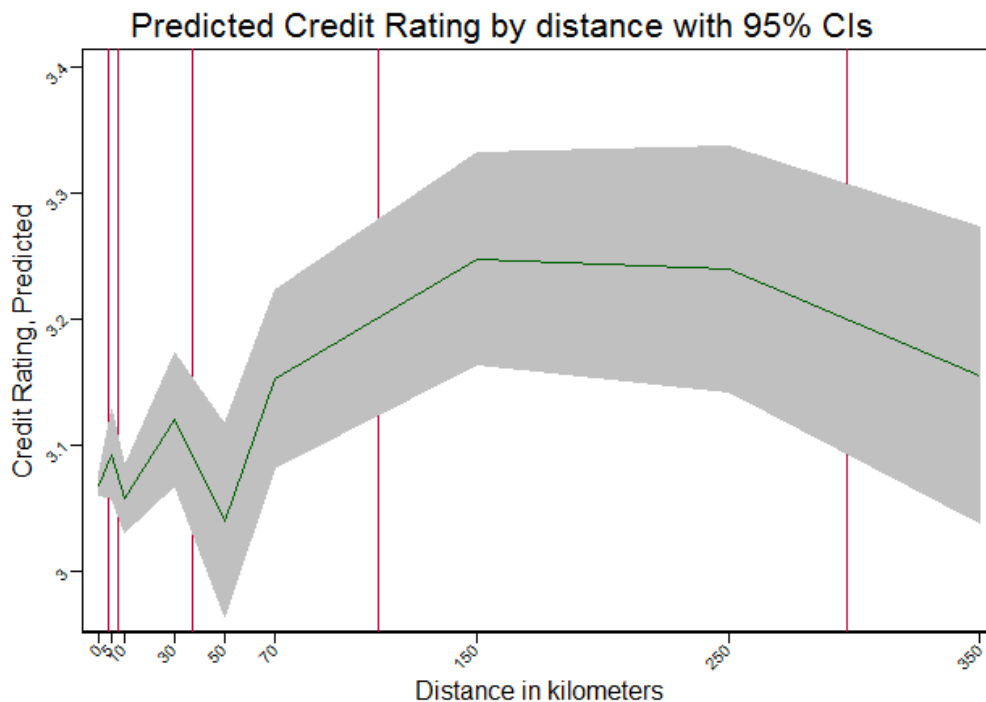


Figure 18 presents the results using distances between zero and 37 km, i.e. 90th percentile of distance. When dealing with distances within this interval, we choose to not use restricted cubic splines on our main variable of interest, but instead run the regression using the logarithm of distance. We find that distance is significant at a 10 % level and as showed above, distances in this interval appear to have little impact on the predicted Z-score. Consequently, we do not find a clear relationship between lending distance and risk in our analysis, using Z-score as a proxy for the risk associated with a loan.

7.2.2. Robustness analysis: Using firms' credit rating as a proxy for risk

Figure 19 *Predicted Credit Rating by distance using the whole sample, with 95% CIs. (The percentiles (and knots) at P65, P75, P90, P95 and P97 are marked with red lines)*



The predicted Credit Rating, illustrated in Figure 19, represent the relationship between risk and lending distance between the borrowing firm and the closest branch of the lending bank.

Like in our main analysis, we do not find a clear relationship between lending distance and the predicted credit rating. Within the first 50 km it is hard to tell whether there is a clear trend, as it rapidly shifts between a positive and negative relationship. In addition, the magnitude seems to be small and therefore we cannot conclude that there is a relationship between lending distance and credit rating, i.e. the risk associated with a loan.

Further, the confidence interval at 95% is somewhat larger than in our main analysis but still seems to be significant, as the standard deviation of *Credit Rating* in our sample is 1.15. Altogether, our findings support that we do not find a clear relationship of economic importance between distance and risk.

We test to see whether the results differ when running the regression on small firms, the economic upturn from 2005 to 2007 and on the observations within the 90th percentile of

distance. In these regressions we observe the same tendencies as in our main regressions. Consequently, this supports that we do not find that increased lending distance is associated with increased risk in our analysis.

7.3. The Effect of Competition on Distant Lending over the Business Cycle

Since we do not find any empirical evidence of a relationship between business cycles and lending distance nor that increased distance is associated with increased risk, we choose to not move forward with the last model in our analysis. Whether competition leads to more distant lending, will not be of any practical relevance in our study, as we cannot use distance as an adequate proxy for risk.

8. Potential Sources of Divergence

Several factors may contribute to our results deviating from literature and our hypotheses.

First, geographical conditions will likely influence the relationship between lending distance and the risk associated with a loan. Granja et al. (2019) found that in the U.S., 80 % of their lending distances were within approximately 80 km, whereas in our sample, 90 % of our lending distances are within 37 km. In addition, the variation of lending distance over the sample period is much greater in the U.S. than in our sample. In the U.S., the average lending distance varies between approximately 160 km and 560 km, while in Norway it varies between 10 km and 40 km. The relatively small variation in lending distance might make it challenging to observe the effect of increased distance in our sample. This is further evident as 50 % of our observations have a lending distance of less than 1.6 km. This may be a consequence of lending distances in Norway generally being small or caused by assumptions made when constructing this variable.

When constructing the distance variable, we assume that it is the closest branch of the lending bank that issues the loan, although we do not have any data that confirm this. However, this assumption is in accordance with practice (Carling & Lundberg, 2005), thus it is not necessarily a very strict assumption. However, it may to some extent be decisive, as lending distance in some cases will appear to be shorter than it really is. Furthermore, the distance is generated as the length of the shortest curve between the centroid of a borrower's postal code and the centroid of a lender's closest branch postal code. This entails that if the closest branch of the lending bank is located in the same postal code as the firm, the distance will equal zero. In Norway, there are large differences in regard to the geographical size of a postal code. For example, the geographical area in Oslo of 426 km² (Thorsnæs, 2019b) is divided into 637 postal codes (Bolstad, 2019b), while the municipality Beiarn, in Nordland, covers an area of 1 179 km² (Thorsnæs, 2019c) which is divided into four postal codes (Bolstad, 2019a). In areas of Norway with similar tendencies as in Beiarn, the lending distance may be registered as zero if the firm is registered in the same postal code as the bank branch, although the actual lending distance may be considerably longer. Consequently, this may lead to biased estimates.

In our analysis, we had access to data covering all loans issued to the corporate loan market in Norway during our sample period. However, we did not have access to all loan applications. We assume that the large proportion of short lending distances may be a consequence of a

higher approval rate for short loans. If we had had information on loan applications, this might have provided a better understanding of whether distance is related to risk. In addition, the small proportion of long lending distance may entail that we do not observe the actual relationship between lending distance and risk at those lending distances.

In contrast to the study by Granja et al. (2019), we choose to study lending distances at the account level and not at the bank level, as we had access to this detailed information in our dataset. By using aggregated data on the bank level, we would have lost a lot of information and variation in our dataset. However, this may be a contributing factor to our results differing from theirs.

Further, our numbers on unemployment, which serves as a proxy for the business cycles, are appointed based on the location of the firm and not the bank. At longer lending distances, the bank's and the firm's respective unemployment numbers may differ. Since a large proportion of our sample has short lending distances, we assume that this is not particularly decisive. However, since the theory implies that lenders abandon caution in the midst of a boom, this may be a source of divergence if banks are more affected by their own state of the business cycle, than the firms'.

When estimating the relationship between risk and lending distance, we use fixed effects. As shown in Appendix 1, we conduct a Hausman test in order to decide whether we should use random effects or fixed effect in our regressions. The Hausman test rejects that the random effects estimator is consistent, hence we cannot use random effects. Therefore, we only analyze the variation within each individual firm and not variation between the firms in our sample. This may affect the significance of the relationship between lending distance and risk in model two. In addition, one can argue that analyzing variation within each firm is not sufficient to assess whether increased lending distance is associated with increased risk.

Finally, we use the dummies on small, medium sized and large firms to control for the firm size based on number of employees when estimating the relationship between lending distance and risk. This removes some of the variation in our sample. However, we do not believe that we would obtain very different results if we were to use the absolute number of employees instead.

9. Concluding Remarks

In this master thesis, we aimed to provide empirical evidence on how competition in the corporate loan market in Norway affect banks' risk taking, through distant lending over the business cycle. We used comprehensive datasets provided by the Norwegian Tax Authorities (Skatteetaten), the Institute for Research in Economics and Business Administration (SNF) and the Norwegian Centre for Research Data (NSD). These datasets contained information on Norwegian firms' accounting data, all loans provided by Norwegian banks, location information, unemployment numbers etc. Several studies have been conducted on the Norwegian banking market. However, to the best of our knowledge, there are no previous studies on how competition affects stability in the Norwegian banking sector through distant lending.

In the U.S., Granja et al. (2019) find a relationship between lending distance and banks' risk taking, and that an increased degree of competition leads to cyclical variation in lending distances. This implies that in a competitive environment, banks are more willing to lend at longer distances during a boom. Thus, it appears that competition has a negative effect on the stability in the banking sector, as competition makes banks more risk-seeking in the boom. This contributes to procyclical lending practices and increasing instability. Banks in competitive environments are thus more vulnerable to fluctuations or shocks to the economy, than banks that do not experience competition.

Our results related to whether there is cyclical variation in lending distances, yield ambiguous results, as they depend on how much of the sample that is included. Collectively, we do not find a clear relationship between business cycles and loan distances, and thus cannot conclude that distances increase in economic upswings, like in the U.S.

Furthermore, we do not find a clear relationship between distance and risk. This may be due to several different factors. First, it may imply that distance is of no importance in regard to risk taking in the Norwegian corporate loan market. In other words, companies are just as risky at short distances as at longer distances, since the risk assessment is equally good when distance increases. This might be a result of technological advancements, good risk management and a generally well-regulated market.

To the contrary, a reason why 90 % of our sample is within 37 km might be due to the fact that lending at longer distances is indeed riskier in Norway. Hence, banks choose to not give out long distance loans, i.e. they have an effective screening of loan applicants. If we had access to information about loan applicants and the approval rates of banks, we could have investigated the relationship between distance, the risk associated with the loan applications and the effectiveness of banks screening, using the approval rate. This may be interesting to investigate in further studies of the relationship between lending distance and risk.

Finally, the reason why we do not find a relationship between lending distance and risk, may be that long lending distances are rare due to good bank coverage in Norway. Norway is a relatively small country, where regional politics are of high priority. Most companies will therefore have bank branches within a relatively short distance. It is also reasonable to assume that distance is an important factor for the majority of companies applying for loans, i.e. geographic distance itself is a matching criterion.

The interaction between good bank coverage, an efficient and well-regulated banking system and improved credit rating technologies might be the reason why we do not find a relationship between lending distances and risk in Norway.

The trade-off between competition and stability in banking is a widely debated topic. If competition leads to more risk taking by banks, it might result in severe financial crisis, like the Norwegian Banking Crisis and the Great Recession. In the event that such a relationship between competition and excessive risk taking, through distant lending, exist, it would imply that targeted regulation is necessary.

Since we did not find a clear relationship between lending distance and risk, we did not consider it beneficial to run our last model on competition. Regardless of whether a correlation is found between increased competition and increased distances, it is not possible to measure whether competition leads to increased risk, as we cannot use distance as a proxy for the risk associated with a loan. Based on our results, we cannot conclude that competition in the Norwegian banking sector has a negative impact on financial stability through distant lending.

Our results are not necessarily surprising in light of the extensive regulations and supervision imposed on Norwegian banks. The regulations and supervision are said to have ensured a solid banking system through the business cycles, both during our sample period and in recent years.

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11. Appendix 1: Methodology

Since our dataset consists of a time series for each corporate loan account between 1997 and 2013, we are dealing with panel data. Unlike cross-sectional and time-series data, panel data are two dimensional (Wooldridge, 2013). This enables us to exploit both cross-sectional and time dimensions in our study, which allows us to study evolutions and identify causal effects concerning risk taking in the corporate loan market in Norway.

When analyzing panel data, we cannot assume that the observations are independently distributed across time. To exemplify, unobserved factors such as special trade agreements, public interests, i.e. subsidies and public guarantees, and personal relations between a firm's management and a specific bank might have an impact on each firm's lending distance or the risk associated with a loan in both year t and $t + 1$. Consequently, even though panel data provides possibilities not available in cross-sectional or time-series data, it is also associated with some econometric issues or implications which we need to address in order to interpret our results causally. In the following, we present different estimation methods and how we control for these econometric implications.

11.1. Estimation methods

We wish to measure how competition affects risk taking, through distant lending, over the business cycle in the corporate loan market. By using panel data, our error term contains unobserved time-constant firm-specific characteristics and unobserved time-varying firm-specific characteristics (Wooldridge, 2013) of each firm j :

$$\varepsilon_{jt} = a_j + v_{jt}$$

Both the time-constant and time-varying unobserved characteristics can be a source of endogeneity in our model, which will cause our results to be biased. When choosing the estimation method, we have to address this issue in order to get an accurate description of our results.

Fixed Effects

Fixed effects only estimate the time-varying effect, hence it only uses variation within each individual group (Wooldridge, 2013). Consequently, the fixed effect approach removes the unobserved time-constant firm-specific characteristics a_j from the estimating equation. We can therefore interpret our results causally even though a_j is correlated with our independent variables, which normally would be a violation of the zero-conditional mean assumption and lead to endogeneity in our model. However, by using fixed effects we cannot measure time-constant effects, e.g. how firm size affect lending distances.

Random Effects

Random effects allow us to estimate the effect of time-constant and time-varying independent variables (Wooldridge, 2013). This enable us to analyze both the variation between and within each individual group. This method is considered more efficient, since it exploits more of the variation in our sample than other estimation methods such as fixed effects.

The essential question when making the choice between fixed- or random effects, is whether our independent variables are likely to correlate with the unobserved factors. Since we include time-constant factors, our error term will include unobservable time-constant firm-specific characteristics. Hence, we have to assume that the unobserved effect a_j is uncorrelated with all our independent variables in all time periods. If else, we will have an endogeneity problem in our model.

Choice of Estimation Method

The Hausman test compares the fixed and random effects model under the null hypothesis that the time-constant unobserved characteristics are uncorrelated with our explanatory variable in all time periods. When conducting the test, we reject the null hypothesis of no correlation and conclude that the random effects estimator is not consistent. Hence, we use fixed effects estimation as our estimation method.

11.2. Heteroscedasticity and Autocorrelation

In order to obtain robust inference, we need the assumptions of homoskedasticity, i.e. the error term has the same variance for any given value of the explanatory variables, and no

autocorrelation, i.e. covarying error terms, to hold. If else, we need to compute standard errors that are robust to heteroskedasticity.

When dealing with panel data, we can allow for autocorrelation in the error term if the number of time periods is not too large, i.e. with time series under 20-30 years (Torres-Reyna, 2007). Next, we test for heteroskedasticity by conducting a Breusch-Pagan LM test. We reject the null hypothesis, which states that the error term has the same variance for any given value of the explanatory variables. In order to compute standard errors that are robust to autocorrelation and heteroskedasticity, we choose to cluster our panel data by each individual firm in all regressions.

12. Appendix 2: Economic Regions

Regions:	Observations:	Firms:	Sum loans in MNOK ³	Distance ⁴	HHI _{region}	Unemployment	ALV ⁵
Sør-Østfold: 11	50 946	1 852	15 463	11.9	2.769	2.63 %	8 241 218
Vestfold: 13	80 507	3 039	20 549	11.0	2.500	2.29 %	6 570 980
Kongsberg: 14	10 502	402	5 201	14.6	3.208	1.55 %	12 252 638
Hallingdal: 15	14 157	481	2 755	21.1	1.857	1.20 %	5 558 505
Valdres: 21	8 483	296	1 181	14.8	3.671	1.09 %	3 981 995
Gudbrandsdalen: 22	15 255	495	1 885	14.6	2.686	1.95 %	3 827 615
Lillehammer: 23	10 755	433	2 797	13.8	4.281	1.70 %	6 835 094
Gjøvik: 24	21 754	774	5 609	10.6	2.346	1.85 %	7 228 664
Hamar: 25	26 585	941	9 988	11.0	3.367	1.98 %	10 390 282
Kongsvinger: 26	16 038	568	3 443	11.5	3.553	2.44 %	5 877 694
Elverum: 27	13 884	498	2 575	13.7	3.092	2.30 %	5 049 981
Tynset/Røros: 28	10 483	341	1 561	16.7	1.940	1.29 %	4 471 541
Nordvest-Telemark: 31	11 056	378	1 165	15.7	1.821	1.81 %	3 060 806
Øst-Telemark: 32	9 436	349	1 471	12.6	2.126	1.95 %	4 234 090
Sør-Telemark: 33	41 033	1 530	9 393	11.9	1.882	2.67 %	6 016 647
Arendal: 34	28 655	1 164	10 061	17.3	2.475	2.49 %	8 651 739
Kristiansand: 35	66 525	2 560	19 649	16.0	1.741	2.21 %	7 190 767
Lister: 36	17 622	615	3 668	13.3	1.763	1.98 %	5 834 669
Stavanger: 41	112 097	4 079	63 617	22.6	1.720	1.81 %	14 972 051
Haugesund: 42	44 001	1 621	18 204	20.8	2.888	2.24 %	10 852 871
Sunnhordland: 43	21 081	726	6 784	19.2	2.253	2.07 %	8 962 490
Bergen: 44	153 789	5 510	95 445	22.8	2.877	2.14 %	16 913 073
Sunnfjord: 51	24 525	821	7 548	13.0	3.197	1.72 %	8 931 688
Sognefjord: 52	11 020	425	2 304	15.2	1.531	1.17 %	5 608 699
Nordfjord: 53	17 665	608	4 231	14.8	2.361	1.91 %	6 873 367
Søndre Sunnmøre: 54	24 078	826	13 275	15.4	2.432	1.97 %	15 344 180
Ålesund: 55	53 398	1 641	21 277	18.3	2.141	1.89 %	12 791 422
Molde: 56	29 668	1 012	9 597	18.7	2.139	1.77 %	9 458 828
Nordmøre: 57	9 007	296	6 560	22.9	3.152	1.62 %	20 654 340

³ Average yearly loan volume in region r

⁴ Average distance between firm j and closest branch of lending bank i in region r

⁵ AVL: Average yearly loan volume of firm j in region r

Kristiansund: 58	15 966	596	5 490	26.4	1.880	2.49 %	9 111 376
Trondheim: 61	102 112	3 633	51 331	27.8	1.738	2.34 %	13 664 786
Midt-Trøndelag: 62	20 760	781	3 730	22.7	3.026	2.64 %	4 644 232
Namsos: 63	18 573	616	2 805	31.2	3.104	2.37 %	4 481 423
Ytre Helgeland: 64	14 018	458	3 449	28.1	2.588	2.46 %	7 391 098
Indre Helgeland: 65	20 169	705	4 867	25.1	3.064	2.32 %	7 039 954
Bodø: 71	34 626	1 131	30 206	36.9	4.609	2.40 %	25 806 792
Narvik: 72	13 654	443	4 645	75.8	2.602	2.09 %	10 866 524
Vesterålen: 73	18 958	608	3 481	85.4	3.892	3.07 %	5 698 814
Lofoten: 74	16 204	541	2 885	40.8	3.090	3.38 %	5 212 424
Harstad: 75	2 615	89	305	76.2	3.374	2.37 %	3 400 111
Midt-Troms: 76	13 128	427	2 254	152.7	3.319	2.07 %	5 289 632
Tromsø: 77	31 773	1 099	23 202	125.0	2.640	2.18 %	20 635 943
Alta: 81	8 819	339	1 742	154.6	3.482	3.19 %	5 507 197
Hammerfest: 82	12 426	430	2 069	87.2	3.098	3.52 %	4 840 439
Vadsø: 83	11 542	409	1 604	78.6	4.019	3.56 %	3 900 134
N	1 309 348						

13. Appendix 3: Norwegian Business Cycles

Figure 20: Norwegian Business Cycles between 1985 and present (*Statistics Norway, 2014*)

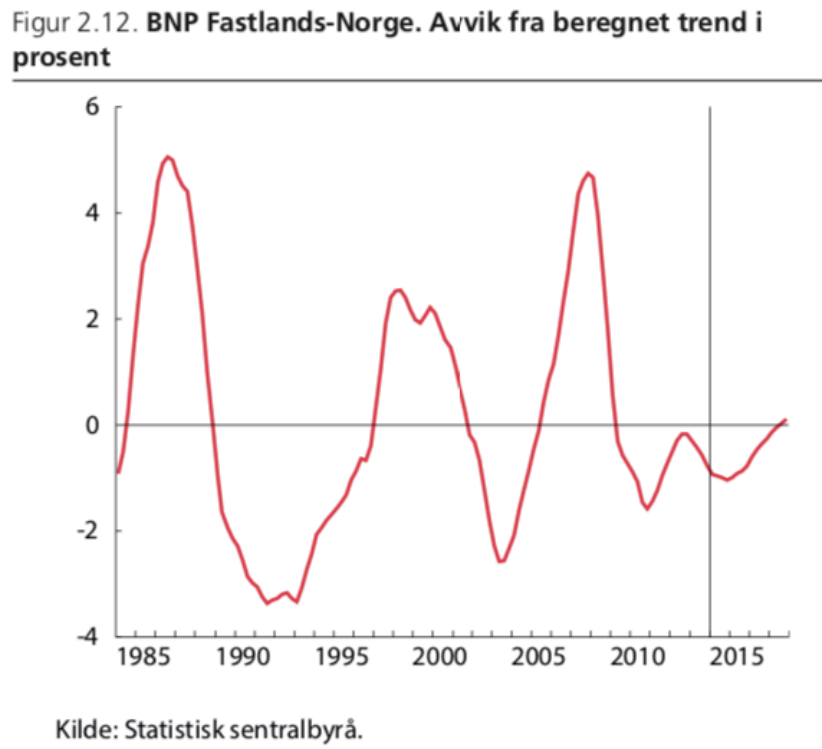


Figure 20 illustrates the Norwegian business cycles from the 1985 until 2014.