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Three essays on competent capital

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Contents

Chapter 1

Introduction

This thesis contains three essays on the economics of competent capital. All papers focus on abilities of those who provide capital, predominantly to small and medium sized enterprises (SMEs). I deliberately use the term “competent capital”, referring to the ability to match capital with relevant business competencies and prospering investment opportunities. The term “competent capital” or alternatively “smart capital” is often used to describe the venture capital model, where investors offer business network and strategy advice together with hard cash in return for a equity share in a start-up company (Hellmann and Puri, 2002). The term is, however, also suitable in a much wider context. Providers of capital that are able to separate good investment opportunities from bad ones, and take advantage of these opportunities over time, are in the possession of “competent capital”.

This competence based concept of capital is closely related to the principal-agent theory in economics (Kaplan and Stromberg, 2001). The capitalist’s competence – or skills - can be split into two components: 1) Outsourcing skills and 2) complementary skills. With ’outsourcing skills’ we think of the capitalist’s ability as principal, i.e. the ability to select suitable agents, monitor them and design contracts that give the agents incentives to manage the capital in accordance with the principal’s interest. With ’complementary skills’ we think of skills of the principal that are complementary to the agent’s. The provider of capital may posit knowledge and experience relevant for marketing, innovation, financing, strategy, business networking, client relations etc., which the agent does not hold. Hence, the competence is complementary.

The pecking order theory explains the preferred order of finance for firms— first retained earnings, then debt, and lastly outside equity —based on the degree of asymmetric information (Myers and Majluf, 1984). The term competent capital, however, extends the pecking order theory by allowing firms’ order of prioritization to depend on what form of financing provides the best mix of price and complementary competencies to the firm (see Sjögren and Zackrisson (2005) for further discussion). Investors with competent capital can run profitable investments in business segments where other financiers do not succeed. The more competent the capital, the larger is also the availability of capital for high quality projects. This result follows from the fact that being more competent enables the investor to reduce risk and generate higher returns within challenging business segments.

In Chapter 2 I study how the availability of competent capital for SMEs depends on the local credit market structure. The term "competent" here relates to the ability of local banks to cut down on informational asymmetries between them and the SMEs they finance. Chapter 3 contains a study of the success of government credit programs in providing innovative projects with competent capital where the private capital market fails. The term "competent" here relates predominantly to the ability of the government to select those cases that have a higher survival and growth probability. Finally, in Chapter 4, I present a study of whether capital becomes less competent as the firm's key personnel— the owner and the manager – grow older. Hence, here I test indirectly how aging affects owner and CEO competence.

The thesis covers the two main agency relationships within the field of finance; the agency relationship between business owners and managers, and the agency relationship between business owners and creditors (see Myers (2001) for a literature review). Chapter 2 on community banking, as well as Chapter 3 on the public lending program, analyze outcomes involving a relationship between firms and their creditors. Although creditors may possess complementary skills to the firms, and for example combine credit provision with financial counselling, the main competence of credit capital is most likely captured by the level of its 'outsourcing skills'. That is, the creditor's (principal) main task is to apply its 'outsourcing skills' in order to assure that the firm (agent) pays back the loan with interests. The business owner is the firm's residual claimant and may therefore want to take on higher risk than the creditor whose payoff is independent of outcome as long as the business does not default. Thus, the studies in Chapter 2 and Chapter 3 apply several proxies for default risk when comparing debtors of community banks and innovation loans, respectively, with firms with other sources of capital. In Chapter 4 on aging owners and CEOs, the owner is the principal, while the CEO is the agent. The study suggests that firm productivity is not affected by owner age, and thus that the competence of capital does not deteriorate with age. The age of the CEO on the other hand does seem to affect productivity, suggesting that it is the abilities of the agent that are affected.

This thesis touches partly upon subjects in corporate finance and partly upon public policy. In the wake of the 2008–09 financial crisis, new international banking regulations have strengthened the solvency and liquidity of the banking system. Community banks have expressed worries that this regulation will entail comprehensive administrative procedures, leaving a competitive disadvantage, as it favors larger banks with economies of scale. This is an interesting backdrop for the results of the study on community banking presented in Chapter 2. Moreover, the financial crisis was seen by many as a severe blow to the unconditional belief in the efficiency of markets, and it has created a new legitimacy for industrial policy (Stiglitz et al., 2013). Consequently, politicians are increasingly concerned with taking an active part in facilitating a business environment that can generate value and wealth. In Chapter 3 I discuss the welfare effects of a public loan program providing credit to innovative projects that do not qualify for loans from the private market. This discussion is particularly relevant since there has been a sharp increase among several OECD countries in the number and size of government loan and guarantee schemes to promote small business credit (OECD, 2009). In Chapter 4 I discuss the potential for welfare improvements through industrial policies that give incentives to replace CEOs at an earlier age. This discussion is relevant in the context of the EU's focus on how to facilitate business transfers to new and younger owners as its population ages.

The studies are all empirical, and benefit from comprehensive panel data provided by the Norwegian business registers. Still, there are challenges related to the availability of data as well as methodological challenges related to causal identification of effects. Many studies within labor and health economics address the identification problem by exploiting exogenous variation from natural experiments. However, in the topics I explore, to the best of my knowledge no such exogenous variation is available. Thus, although I aim at controlling for possible sources of biases in the analyses, the identification strategy sets limits to the extent that the results can be interpreted as causal relations. The remaining part of this introductory chapter briefly presents each paper in more detail.

1.1 Community banking and the market for business credit.

Berger and Udell (2006) challenge the conventional paradigm that small local banks have an advantage in serving small informationally opaque businesses with credit. Rather, they predict that whether small banks have an information advantage in lending will depend on whether more advanced transaction technologies are feasible and profitable for larger banks operating in the same market. Supporting this prediction, Berger et al.

(2014) find that small opaque firms in the US are not more likely to have a community bank as their main lending bank.

I test the predictions of Berger and Udell (2006) on Norwegian data. Norway is a country where advanced transaction-based lending technologies are both feasible and profitable, and it is thus a highly relevant example in comparing relationship lending from community banks with transaction based lending typically applied by larger banks.

The empirical design of the study is modelled in terms of three steps or research questions. First, I test whether a high community bank market share in a local market correlates with a higher probability of small businesses having long-term loan financing. If community banks have an advantage in lending to small opaque firms I should find that firms located in municipalities with a high market share of community banks will have a higher probability of receiving long term loan financing. Second, I test whether small businesses located in local markets with a high community bank market share receive more credit than in local markets with a lower community bank market share. The literature on relationship banking predicts that firms which receive loan financing from firms specialized in relationship banking, such as community banks, also receive more loan financing (see e.g. Petersen and Rajan (1994)). Third, I test whether small businesses with community bank loans perform better or worse as compared to businesses with loans from other types of credit institutions. Comparing firm performance is important as it indirectly tests whether community banks have an informational advantage or whether they simply take on more risk. For example, assume that firms located in areas with a high community bank market share more frequently have long term loan financing and that they also receive more loan financing given that they have loan financing. If it then turns out that these firms more frequently become inactive, go bankrupt or run with operational deficits then this indicates that community banks do not have an informational advantage, but rather that they take on more risk.

The study shows that the share of firms receiving a loan, as well as the amount of credit granted, increases with the market share of community banks in the local market. This is in contrast to Berger et al. (2014) who suggest that community banks have lost their advantage in relationship lending due to progress in lending technologies. Furthermore, I do not find evidence suggesting that firms with community bank financing are more likely to run with operational deficits, become inactive or go bankrupt. I interpret the combination of more credit and no increased risk of deficits, inactivity, or bankruptcy as support of the hypothesis that community banks still have an informational advantage compared to larger banks in the market for small business lending.

The study does not have an experimental design that implicitly controls for reverse causality. A possible concern with my conclusion is that community banks might be self-selected into areas with a particularly high demand for credit. The historical evolvement of the Norwegian credit market suggests, however, that we would not expect community banks to be located in areas with a higher demand for credit compared to regional and national banks. Thus, I argue that the results are not likely to be a case of reverse causality.

The bank credit data for different categories of creditors and debtors applied in this study are aggregated at the municipality level. Ideally we would want to have firm level data on the relationship between the bank and firm. For example, when testing the performance of firms with community bank loans compared to businesses with loans from other types of credit institutions, I am limited to comparing firms located in areas with a high market share with firms located in areas with a low share. This creates a measurement error in the analysis. However, robustness tests with respect to the market share cutoff points for defining community bank portfolio firms suggest that the measurement error does not affect the results qualitatively.

Part of the analysis in this paper is conducted on cross section data. With panel data one could have controlled for firm fixed effects, including which municipality the firm is located in. A challenge with this type of method is that there are many reasons for a marginal change in the community bank market share. Thus, in order to test whether community banks have an informational advantage one would need a detailed model that controls for whether changes in the community bank market share are supply or demand driven. For example, if the community bank market share increases because the supply of credit from larger banks decreases then one would not expect this to have a positive impact on the availability of firm level credit. However, if the community bank market share increases because the community bank increases its supply, then we would expect to see an increased availability of credit for small opaque firms.

1.2 Partly risky, partly solid – performance study of public innovation loans.

Public credit programs are appealing to policy makers as they give leverage to public fund, have limited up front costs, and have liabilities that are contingent and pushed into the future (Honohan, 2010). Despite the global proliferation of publicly financed loan and guarantee schemes, the documentation on the effectiveness of such policies is scarce and the results are ambiguous (Warwick and Nolan, 2014; Valentin and Wolf, 2013; Samujh et al., 2012; Beck et al., 2008).

Several effect studies of private sector development programs apply propensity score matching (PSM) to identify control groups that prior to treatment are as similar as possible to the program participants (see e.g. Oh et al. (2009), Norrman and Bager-Sjögren (2010), Uesugi et al. (2010), Foreman-Peck (2013)). The control groups selected with PSM, however, fail to address non-observable firm characteristics that are potentially important for the self-selection into the program and/or being selected by the program administrators.

This paper presents an effect study on the performance of firms with an innovative project receiving funding from the Norwegian publicly financed and administrated direct lending program— "the innovation loan program". I approach the problem with non-observable sources of bias by applying three different control groups which all have inherent characteristics addressing potential problems with these sorts of sample selection biases. The first control group contains firms which applied for innovation loans but were rejected, the second control group consists of firms which received loans from a private credit institution, while the third control group are firms with venture capital financing.

Takalo (2009) emphasizes that any public innovation policy tool should be judged on whether it yields an expected net increase in social welfare. However, most impact studies aim at measuring the counterfactual outcome— what would have happened to the firms had they not received loan financing from the public program? I also try to measure the counterfactual outcome of not receiving an innovation loan. My main focus, however, is on output measures— such as survival, profitability and growth in sales, value added and employment —applying control groups that serve as benchmarks of the alternative use of resources outside the program.

Comparing the firms that received innovation loans with program rejects, I find that the program participants have a stronger post-treatment performance. This can be considered a first test with respect to whether the program is successful in improving welfare. If there had been no differences between the treated and the rejects, then this would be a strong indication that the program is redundant with respect to financing innovative projects. Comparing the firms that received innovation loans with firms with private market bank loans I find only weak evidence of differences in firm value added growth, despite a higher probability of becoming inactive. Finally, comparing the firms with innovation loans with venture portfolio companies I find no statistically significant differences with respect to the growth in sales. However, stronger growth in employment and assets among the venture portfolio companies may indicate that they are more likely to succeed in the long run compared to the firms with innovation loans.

The results suggest that in order for the program to provide welfare on the same level as regular business credit, the positive knowledge spillover effects from the innovation loan projects must compensate for the subsidy element of the program. The subsidy element covers the higher propensity to become inactive among the innovation loan program participants, and amounts to about one third of the credit provided by the program adjusted for rents and the social cost of public funds. Comparing with venture portfolio companies there are only weak indications that the firms with innovation loans perform weaker. This indicates that the innovation loan program provide the same level of welfare as venture funds given that the knowledge spillover effects are on the same level. It should be noticed that the average return of early stage European venture funds has been zero or negative the past 20 years (EVCA, 2014). This suggests that it is a difficult environment for innovative projects to succeed in general, and not only for the innovation loan program in particular. The latter raises the question whether it is at all possible to ex-ante identify welfare enhancing innovative projects with sufficient precision.

It is challenging to find a control group which provides an unbiased estimate of not receiving an innovation loan, everything else equal. The estimated treatment effect based on the comparison of program participants with program rejects in this paper is likely to include an administrative bias as the program participants are not randomly selected among the pool of applicants. Hence, this comparison can only be considered as an upper bound of the program's effect, as the projects selected by the program administrators presumably are better than those rejected on average, even after controlling for observable characteristics.

Several approaches that could control for this administrative bias were considered. One approach considered was to use exogenous variation in the innovation loan program's budget over time. This could open up for a "regression discontinuity" type of design, comparing the marginal rejects in a year with small budgets with marginal participants in years with more generous budgets. Due to the "first come, first served" selection practices of Innovation Norway and how firms are guided to the different programs depending on available budgets before sending in a formal application, the regression discontinuity approach is, however, not suitable. Another possible approach considered, inspired by recent quasi experimental studies within labor and health economics, is to use the assigned loan officer for assessing the application as an instrument of whether the firm received support (see e.g. Dahl et al. (2013)). The idea is that if the applications for project support are randomly assigned to different loan officers, then one could use more pessimistic clerks as an instrument for whether the application was rejected. Again, this approach was not feasible as more experienced loan officers are systematically allocated the most complex applications, and thus the choice of the loan officer is not random.

1.3 Aging business owners' and CEOs' impact on firm performance.

Building on Schumpeter's 1934 seminal work, there is an extensive empirical and theoretical literature focusing on how businesses are created. Particularly, it is now well documented that people are less likely to start a new venture and become entrepreneurs after they pass a certain age (Parker, 2009; Kautonen et al., 2014). Few studies, however, focus on what happens with the venture in the final stages of the entrepreneur's life cycle. This paper is novel, as it focuses on how firm performance is affected when the owner and the management grow old. While most empirical studies do not distinguish between the owner and the CEO, lumping them together under the label "entrepreneur" (Parker, 2009), part of the novelty in this paper is that I try to separate the age effect of the owner from that of the CEO.

Based on a fixed effect model covering the years 2000–09 for firms with a majority owner, I find that the aging of owners, as well as CEOs, leads to a gradual reduction in firm level investments and employment. The negative effects from CEO age on firm employment and CEO age on firm investments seem to start in the CEO's late fifties and early sixties, respectively. For aging owners I identify a negative effect on firm investments for owners older than 60 years of age, the point estimate is, however, only statistically significant for owners between 71 and 75 years of age. Similarly, for employment I find a negative effect of owner age on employment for owners older than 65 years of age. The point estimate is, however only statistically significant for firm owners between 66 and 70 years of age. The results are robust controlling for firm fixed effects, ownership transfers, change of CEO as well as firm age and business cycles.

I also find statistically significant effects of aging CEOs on firm value added. Much of the reduction in value added is due to a down scaling effect, following a reduction in labor and capital inputs into production. Part of the reduction in value added, however, is due to a negative effect on firm level productivity. While a down scaling of the firm's production due to fewer employees and less capital can be a healthy market mechanism leading to a reallocation of resources from down scaling firms to growing firms with higher productivity, a reduction in firm level productivity involves a less efficient use of resources by definition. I do not find any statistically significant effects from owner age on firm value added or productivity. This, may suggest that competent capital does not deteriorate with age.

Taken at face value, the decline in value added of the firms due to reduced productivity associated with aging CEOs represents 0.2% of Norwegian mainland GDP. Whether it is desirable, or even possible, from the social planner's point of view to replace incumbent CEOs at an earlier age depends on the availability of alternative younger managers with suitable profiles, the size of the firm, as well as whether the incumbent CEO can find alternative productive occupations either within or outside the firm. This suggests that potential policy measures aiming at increasing firm productivity by replacing aging CEOs should not be directed towards small firms where the CEO does not have productive outside options.

References

Beck, T., A. Demirgüç-Kunt, and V. Maksimovic (2008). Financing patterns around the world: Are small firms different? *Journal of Financial Economics 89*(3), 467–487.

Berger, A. N., W. Goulding, and T. Rice (2014). Do small businesses still prefer community banks? *Journal of Banking & Finance 44*, 264–278.

Berger, A. N. and G. F. Udell (2006). A more complete conceptual framework for SME finance. *Journal of Banking & Finance 30*(11), 2945 – 2966.

Dahl, G. B., A. R. Kostol, and M. Mogstad (2013). Family welfare cultures. Technical report, National Bureau of Economic Research.

EVCA (2014). 2013 pan-european private equity performance benchmarks study.

Foreman-Peck, J. (2013). Effectiveness and efficiency of SME innovation policy. *Small Business Economics 41*(1), 55–70.

Hellmann, T. and M. Puri (2002). Venture capital and the professionalization of start-up firms: Empirical evidence. *The Journal of Finance 57*(1), 169–197.

Honohan, P. (2010). Partial credit guarantees: Principles and practice. *Journal of financial stability 6*(1), 1–9.

Kaplan, S. N. and P. Stromberg (2001). Venture capitalists as principals: Contracting, screening, and monitoring. Technical report, National Bureau of Economic Research.

Kautonen, T., S. Down, and M. Minniti (2014). Ageing and entrepreneurial preferences. *Small Business Economics 42*(3), 579–594.

Myers, S. and N. Majluf (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics 13*(2), 187–221.

Myers, S. C. (2001). Capital structure. *Journal of Economic perspectives*, 81–102.

Norrman, C. and L. Bager-Sjögren (2010). Entrepreneurship policy to support new innovative ventures: Is it effective? *International Small Business Journal 28*(6), 602–619.

OECD (2009). The impact of the global crisis on sme and entrepreneurship financing and policy responses.

Oh, I., J.-D. Lee, A. Heshmati, and G.-G. Choi (2009). Evaluation of credit guarantee policy using propensity score matching. *Small Business Economics 33*(3), 335–351.

Parker, S. C. (2009). *The economics of entrepreneurship.* Cambridge University Press.

Petersen, M. A. and R. G. Rajan (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance 49*(1), 3–37.

Samujh, H., L. Twiname, and J. Reutemann (2012). Credit guarantee schemes supporting small enterprise development: A review. *Asian Journal of Business and Accounting 5*(2), 21–40.

Schumpeter, J. (1934). *The theory of economic development.* Harvard University Press.

Sjögren, H. and M. Zackrisson (2005). The search for competent capital: Financing of high technology small firms in Sweden and USA. *Venture Capital: An International Journal of Entrepreneurial Finance 7*(1), 75–97.

Stiglitz, J. E., J. Y. Lin, and C. Monga (2013). The rejuvenation of industrial policy. *World Bank Policy Research Working Paper* (6628).

Takalo, T. (2009). Rationales and instruments for public innovation policies. Technical report, ETLA discussion paper.

Uesugi, I., K. Sakai, and G. M. Yamashiro (2010). The effectiveness of public credit guarantees in the Japanese loan market. *Journal of the Japanese and International Economies 24*(4), 457–480.

Valentin, A. and B. Wolf (2013). Credit guarantee schemes and their impact on SME lending: Existing literature and research gaps. *International Journal of Entrepreneurial Venturing 5*(4), 391–405.

Warwick, K. and A. Nolan (2014). Evaluation of industrial policy.

Chapter 2

Community banking and the market for business credit [1]

Abstract: I show that the probability that small businesses are granted credit, and the amount of credit granted, increase with the market share of community banks. Moreover, comparing small firms with community bank finance with corresponding firms with financing from larger banks, I do not find statistically significant differences in the probability of firms going out of business. Contrary to recent findings by others, my results suggest that community banks have an informational advantage in the market for small business lending, despite the application of modern transaction-based lending technologies by larger banks.

2.1 Introduction

In his speech at the Independent Community Bankers of America's National Convention and Techworld in March 2009, Ben Bernanke emphasized the competitive advantage of community banks in providing credit to small businesses, stemming from an in-depth knowledge of their local markets and a commitment to tailoring unique credit products for their customers.[2] At the time of Bernanke's speech, average bank size had systematically increased for more than three decades, primarily through mergers and acquisitions involving small community banks (see e.g. DeYoung et al. (2004)). In the wake of the financial crisis, banks are now faced with stricter capital requirements. The new regulation entails comprehensive administrative procedures which are likely to put

[1] I am indebted to my supervisors Steinar Holden and Leo A. Grünfeld for instructive guidance. Two anonymous referees have also made valuable comments. I thank the Research Council of Norway for part-financing my research. This paper is based on analyses performed for a study originally commissioned by the Eika Group — an alliance of 75 Norwegian savings banks. All remaining errors are mine.

[2] See link `http://www.federalreserve.gov/newsevents/speech/bernanke20090320a.htm`

community banks at a disadvantage, as the costs per loan are disproportionately larger for smaller banks without economies of scale.[3] In the US there is a considerable public policy concern that the new regulation will give another boost to the consolidating trend within the banking sector, resulting in reduced availability of credit for small businesses.

The conventional paradigm, as put forward by Bernanke, that small local banks have an advantage in serving small informationally opaque businesses with credit has however recently been called into question. Berger and Udell (2006) stress that the main reason why previous studies have come to the conclusion that small financial institutions are at an advantage in lending to opaque small businesses, is because transaction lending technologies based on hard quantitative information have been treated as a homogenous group of technologies. They claim that transaction technologies such as small business credit scoring, asset-based lending, factoring, fixed-asset lending and leasing are all technologies targeted at opaque borrowers applied by the larger banks. Thus, they predict that whether small banks have an information advantage in lending to opaque firms will depend on whether such transaction technologies are feasible and profitable for larger banks. Supporting this prediction, Berger et al. (2014) find that small opaque firms in the US are not more likely to have a community bank as their main lending bank. Furthermore, based on a survey of 12 developed and developing countries, De la Torre et al. (2010) find that all types of banks focus on the SME segment. Both studies seem to contradict the conventional paradigm that large banks on a general basis have a disadvantage in lending to small firms.

The fact that large banks are strongly present as lenders to small informationally opaque firms does, however, not tell us whether they are at an informational disadvantage or not, compared to community banks. In fact, Cotugno et al. (2013) find that characteristics of community banks, such as bank size, distance and intensity of labor, are positively associated with the quality of the loan portfolio.

This paper takes the study of community banking and information asymmetry advantages one step further. I map the availability of credit in the small business segment using the local credit market structure as an explanatory factor, and I compare the performance of small businesses over time depending on whether the credit to the business is provided by community banks or larger credit institutions. Consequently, I am able to provide evidence on whether more generous availability of credit to opaque small businesses tends to affect the expected performance of the firms. If community banks are able to provide credit to firms which would not have received debt financing from

[3] In order to quantify the costs of increased regulation The Federal Reserve Bank of Minneapolis has created an online regulatory cost calculator for community banks. See Feldman et al. (2013) for details on the analysis allowed by the calculator.

larger banks without any sign of a poorer selection of firms, then this suggests that the community banks have important information that the larger banks do not.

The study is based on a unique micro dataset covering all banks and their credit supply to all small businesses in Norway per 2011. 2011 was the most recent data available at the time the analysis was performed. The database covers both credit information, accounting data for small businesses and location data splitting the country into 428 local markets (municipalities).

Norway per 2011 is a country where advanced transaction-based lending technologies are both feasible and profitable, and thus a highly relevant example in comparing relationship lending from community banks with transaction based lending from larger banks. In the 2013 Doing Business ranking by the World Bank, Norway is ranked as number two in the world with respect to resolving insolvency and number four with respect to enforcing contracts. In the latest edition of the Financial Development Index from 2012 presented by the World Economic Forum, Norway ranks number 10 with respect to the strength of auditing and reporting standards. Hence, if Berger and Udell (2006) are correct about new transaction based lending technologies removing the small bank advantage for lending to informationally opaque small firms, I would not expect to find any signs of a community banking information advantage in the Norwegian market for small business credit.

The empirical design of the study is modelled in terms of three steps or research questions. First, I test whether a high community bank market share in a local market correlates with a higher probability of small businesses having long-term loan financing. Second, I test whether small businesses located in such local markets receive more credit than in local markets with a lower community bank market share, conditional on actually being granted long-term debt. Third, I test whether small businesses with community bank loans perform better or worse compared to businesses with loans from other types of credit institutions.

The study shows that the share of firms receiving a loan as well as the amount of credit granted increase with the market share of community banks in the local market. This is in contrast to the findings of Berger et al. (2014) that community banks have lost their advantage in relationship lending. Furthermore, I do not find evidence suggesting that firms with community bank financing are more likely to run with operational deficits, become inactive or go bankrupt. I interpret the combination of more credit and no increased risk of deficits, inactivity, or bankruptcy as support of the hypothesis that community banks still have an informational advantage compared to larger banks in the market for small business lending.

A possible concern with this conclusion is that the results are caused by reverse causality, in the sense that community banks are located in areas with a particularly high demand for credit. The historical evolvement of the Norwegian credit market suggests, however, that we would not expect community banks to be located in areas with a higher demand for credit compared to regional and national banks. Thus, I argue that the results are not likely to be a case of reverse causality.

The paper is organized as follows: Section 2.2 briefly presents theoretical and empirical literature related to the advantages and disadvantages of community banking. In Section 2.3 I describe the historical background for the current community bank structure in Norway. Section 2.4 presents the data and descriptive statistics, in Section 2.5 I discuss the methodological approach and present the regression results related to the research questions outlined above. In Section 2.6 I conclude on the results. Summary statistics, robustness tests and variable definitions are attached in table format in Appendix A.1.

2.2 Literature review on information asymmetries and community banking

Myers and Majluf (1984) developed the ”pecking order theory” explaining firms' tendency to rely on internal sources of funds and to prefer debt to equity when they need external financing. Stiglitz and Weiss (1981) point out that small informationally opaque firms in need of external finance are likely to be faced with credit rationing. More recent studies also suggest that the availability of debt depends on the type of credit institution granting it. In a cross country sample of 49 nations, Berger et al. (2004) find that greater market shares of community banks are associated with higher SME employment and more overall lending in both developed and developing nations. Moreover, Mudd (2013) finds in a cross country study that the likelihood of small firms using bank financing is positively associated with the market share of small banks in the country.

Berger et al. (2005) suggest that smaller banks are better at collecting and making use of soft information in their screening process. They find that small banks lend at a shorter geographical distance, interact more personally with their customers, have longer and more exclusive relationships, and alleviate credit constraints more effectively than larger banks. In fact, based on a Japanese survey on firms and their loan officers, Uchida et al. (2012) find that loan officers at small banks produce more soft information than their colleagues at larger banks. Stein (2002) and Berger and Udell (2002) argue that small banks have a comparative advantage in processing soft information as they usually are less hierarchical with fewer levels of management between the loan officer and the loan decision-maker. This hypothesis is supported by Canales and Nanda (2012) who find, based on a Mexican data set, that decentralized banks give larger loans to small firms and those which require soft information. However, they also find that the more market power the decentralized banks have, the more likely they are to cherry pick customers and restrict the availability of business credit.

Agarwal and Hauswald (2010) find that the proximity between borrower and lender facilitates the collection of soft information which leads to more credit being available to firms, but at a higher price. A recent study by Herpfer et al. (2015) on Norwegian data, exploiting exogenous shocks in travel distances, also find results suggesting that proximity between firm and lender increases the price of credit. They, however, find evidence suggesting that higher prices in turn reduces the credit demand. The study also find that proximity is likely to increase the probability of a credit relationship. The results are argued to be consistent taking into account that the firm's gains from reduced transaction costs due to increased proximity exceeds the increased borrowing costs.

Asymmetric information in the market for firm credit is closely related to the concept of relationship lending. The difference between relationship lending and normal screening is that with relationship lending the bank can monitor the borrower closely over time, acquiring customer-specific information only available to the firm itself and the bank. Relationship lending is typically based on a loan officer gathering soft information by observing the firm's performance on all dimensions of the banking relationship including information on the firm's owners, suppliers, customers and competitors. Community banks are likely to have an advantage in relationship banking as the bank's ability to gather private information is better with shorter distances between lender and borrower (Hauswald and Marquez, 2006).

Berlin and Mester (1998) and Boot (2000) suggest that one benefit of relationship banking is that the lender can provide intertemporal smoothing of contract terms, giving subsidized loan financing to young firms because the informational advantage will provide the bank with rents in the long term. This way relationship lending can mitigate the problem of adverse selection of young firms searching for financing (Petersen and Rajan, 1995). The flip side of the coin is that relationship banking can lead to a hold-up problem for the firm. As first pointed out by Sharpe (1990) and Rajan (1992), the hold-up problem arises as the bank gains private information about the firm which it in turn takes advantage of by charging monopoly rents from the firm. Yet, Petersen and Rajan (1994) find no evidence of abuse of monopoly power on rents. Rather they find that close ties with a credit institution increase the availability of financing. Thakor (1996) provides a formal theory along these lines. Cotugno et al. (2013) also find that relationship lending is associated with higher portfolio quality, measured by default risk.

The latter is interesting, as one could also believe more informed lenders to be willing to accept higher risk as long as the risk was compensated by higher interest rates.

There are theoretical arguments based on other factors than informational advantages which can explain a potential advantage of community banks in financing informationally opaque small businesses. In their seminal paper, Dewatripont and Maskin (1995) develop a model which explains how small banks with a decentralized credit structure can get a self-selected group of high quality projects. The rationale here is that small banks have limited funds, and thus credibly can refrain from refinancing projects which do not succeed after the first round of financing. In comparison, larger banks with a larger and more centralized capital structure are likely to have soft budget constraints which in turn also attract entrepreneurs with lower quality projects more likely to need refinancing. Related to the theoretical predictions of Dewatripont and Maskin (1995), Benvenuti et al. (2010) find that the decentralization of authority increases bank lending to small firms.

2.3 The historical development of Norwegian community banks

In order to understand the current credit market structure it is important to know the historical development of the Norwegian banking sector. I argue that based on how the Norwegian banking sector has developed over time one should not expect today's community banks to be located in areas with a higher demand for credit compared to banks that operate regionally or nation-wide.

The first Norwegian savings banks were established in the largest towns of Norway in the early 1820s. This followed a trend from continental Europe starting a few years earlier. The savings banks were typically established by the town's bourgeoisie; government officials and tradespeople. The mission statement of the savings bank typically focused on the bank's role in collecting deposit services and how this was an important means to fight poverty. Svendsen et al. (1972), however, emphasize that another target objective that was just as important was to improve the availability of credit financing for the same bourgeoisie.

In the following hundred years there was a continuous increase in the number of banks and amount of capital under management of savings banks (Svendsen et al., 1972). In 1900 there were 413 savings banks and 82 commercial banks in Norway. From the interwar period and until the early 1960s the Norwegian credit market structure was fairly stable. In 1960 there were about 600 savings banks of which the vast majority would qualify as community banks. This meant that most municipalities in Norway had their own savings bank.

In the 1960s there was a big national reform reducing the number of municipalities from 745 to 453, and this in turn made it natural to consolidate banks within the same municipality. By the early 1980s the number of savings banks had been halved, and the first regional savings banks had been established.

Following a deregulation of financial markets combined with low fixed interest rates, the Norwegian banking sector went through a boom period during the 1980s (Moe et al., 2004). From 1983 to 1987 the amount of credit provided by Norwegian banks increased from NOK 157 billion to 415 billion, nearly tripling over a period of four years (Torsvik, 1999). The boom combined with increased loss ratios and falling asset prices led many banks into economic difficulties.

The number of Norwegian savings banks, most of them typical community banks, was reduced from 270 in 1980 to 134 in 1991, which is about the same number as today. The reduction in the number of savings banks can partly be explained by a consolidating trend, but was also due to economic problems following an expansive credit strategy during the 1980s. These effects combined led to a new banking structure with ten regional banks covering 70% of the Norwegian credit market.

Covering the period from the deregulation in the 1980s until 2005, Ostergaard et al. (2009) find evidence suggesting that the level of social capital, competition with other banks as well as the bank's capitalization are the most important factor for whether savings banks remain independent community banks. They find that savings banks which operate in areas with high social capital are better at internalizing the interest of their local community and less likely to face opportunistic behavior from their customers. Their definition of independent savings banks is very similar to the definition of community banks in this paper.

To sum up, Norwegian community banks seem to have emerged in areas where there was a demand for credit services, deposit services, or both (Svendsen et al., 1972). There does, however, not seem to be a common pattern why community banks cease to exist. The community banks that have disappeared since the 1960s are today part of larger community, regional or national banks. The wave of mergers in the 1960s and 70s was a top down process largely driven by political initiatives and the Norwegian Savings Banks Association, independent of fundamental market forces. In fact, most of the merged community banks remained de facto autonomous within the larger entities, and economies of scale were limited to the centralization of some administrative tasks. The fact that the governance of community banks normally has tight relations to the municipal administration makes consolidation processes highly political. During the 1980s those community banks that had practiced an expansive credit policy experienced that their strategy backfired, and several of these ended up being acquired in mergers with larger solvent regional and national banks. Thus, if anything this suggests that the regional and national banks acquired community banks located in areas with a high demand for credit. The results of Ostergaard et al. (2009) suggest that the community banks that remained independent in the period from the late 1980s to the mid-2000s tended to be well capitalized, located in areas with high social capital and/or areas with low competition between banks. While well capitalized banks may imply that these are banks located in areas with a vibrant credit demand, low competition, on the other hand, suggests that they are located in areas less attractive to larger banks most likely due to a moderate demand for credit. Finally, in general there have been considerable changes in the geographical composition of the Norwegian industry structure over the past 200 years. Areas with a high demand for capital during the 19th and early 20th century are not necessarily the same areas that have a high demand for fresh credit today. In particular, Kim and Vale (2001) find evidence that Norwegian banks use the establishment of branches as a strategic variable, and that there is quite a lot of dynamics in the Norwegian network of bank branches. Based on these arguments there is no reason to believe that today's community banks are located in areas with a higher demand for credit compared to banks that operate regionally or nation-wide.

2.4 Data and summary statistics

In my data set, I combine firm level accounting information from the Brønnøysund Register Centre with bank credit balance data from the Norwegian Tax Administration. The firm level register contains all Norwegian firms required to prepare accounts. One-man businesses below a certain threshold of economic activity have simplified rules for keeping annual accounts and are thus not included in the sample. The bank balance data are aggregated at the municipality level for different categories of creditors and debitors. Creditors are split between community banks and other banks. There are 428 municipalities in Norway. Within each municipality the amount of community bank credit is split between three groups of firms according to their size measured by number of employees. Based on these categorizations in the data set there are all together 1 238 unique combinations of community bank credit data.

The sample is limited to small firms with one to 50 employees. The respective categories are 1–10 employees, 11–20 employees and 21–50 employees. Firms with more than 50 employees are rarely financed by community banks. This is natural as community banks do not have a sufficient capital base to provide large loans. Moreover, investment and financial firms, including real estate, are excluded from the sample. I exclude financial and real estate firms because these are firms for which the credit institution easily can identify assets which can serve as collateral. My sample is cross section and consists of 92,151 firm level observations in 2011. 2011 was the most recent bank balance data available at the time the analyses were conducted.

The credit data stems from a sample of 128 Norwegian banks of which 95 are defined as community banks (local savings banks). In the US, a community bank is commonly defined as an independent bank holding less than USD one billion in bank assets (DeYoung et al., 2004). More generally, community banking is a term associated with relationship banking, proximity between lender and borrower as well as decentralized capital structures. DeYoung et al. (2004) also propose a more qualitative definition; *"A community bank is a financial institution that accepts deposits from and provides transaction services to local households and businesses, extends credit to local households and businesses, and uses the information it gleans in the course of providing these services as a comparative advantage over larger institutions"*.

The categorization of community banks in this study was made by the Eika Group, an alliance of Norwegian independent community banks. Both definitions outlined above are consistent with the categorization made by Eika. The banks categorized as community banks by Eika are characterized by their deep roots in the municipality. These banks typically have in their statutes that they shall focus their provision of credit towards firms and private individuals from the local community. Nearly all of the community banks in the sample take on the same name as the municipality in which they were founded, then followed by "savings bank". Savings banks are foundations, most of them are completely self owned entities while others are partly externally owned[4]. With respect to the size of bank assets there are only three community banks in the sample with total assets above USD one billion. The largest bank in the sample had approximately USD 1.5 billion in total assets.

The descriptive statistics of the sample of firms is displayed in Table A.1 in the appendix. Based on credit balance data I calculate the relative share of community bank loans in the municipality for firms with 1–10, 11–20 and 20–50 employees, respectively. The community bank market share can take on values between 0 and 1. It is measured as the number of loans from community banks relative to the overall number of loans to firms of that particular size. I choose to measure community bank market shares in terms of number of loans because it is more robust than market shares in nominal amounts. The

[4]Since 1987 savings banks are allowed to increase their equity by issuing so called Primary Capital Certificates. The certificates entitle the owner to residual claims on parts of the savings bank's surplus. See Ostergaard et al. (2009) for more on this.

descriptive statistics is reported for each of the firm size categories separately. The mean value of the dummy variable for long term loan from credit institution tells us the share of firms with long term loan financing in the sample. This is the dependent variable in the first regression analysis presented in Section 2.5.1. The table shows that the share of firms with long term credit financing is increasing with firm size. The community bank market share is highest for smaller firms with 1–10 employees and gradually decreases with firm size. This is natural as community banks do not have a sufficient capital base to give large loans.

The accounting data applied in this study are at an unconsolidated level. This means that subsidiaries' results are not included in the mother company's results. About two thirds of the firms are independent entities without a mother company or a subsidiary. As a robustness test I perform regressions on the sub sample of unaffiliated firms. The descriptive statistics describing the sub sample of firms without a mother company or a subsidiary can be found in Table A.2 in Appendix A.1. Comparing the statistics presented in Table A.2 with the full sample statistics presented in Table A.1 the sample characteristics are quite stable. This indicates that excluding firms with mother company or subsidiaries should have little or no impact on the regression results.

Moreover, I also perform regressions on a sub sample of firms with a single majority owner. This allows me to include control variables in the regression related to the firm owner. The descriptive statistics of this sample is displayed in Table A.3 in the appendix. In addition to firm statistics of the sample, the table reports firm owner portfolio characteristics both with and without financial and real estate firms. Among other things, the table shows that the median firm owner only has one portfolio company, while the mean firm owner has 2.5 firms in his portfolio. The mean firm owner has 1.9 firms located in the same municipality. This is interesting because the community bank is then likely to gain information about the firm's ability to handle a loan by observing the other firms in the owner's portfolio. The table also reports the share of owners which have had a portfolio company involved in a bankruptcy the past ten years.

2.5 Empirical methodology and results

I perform three types of regression analysis. First I look into firms' probability of having long term credit finance depending on the market share of community bank financing within the municipality. Second, I investigate the amount of long term credit granted depending on the community bank market share in the area. Finally, I look into whether I can identify any differences in performance for firms with community bank financing compared to firms with alternative long term credit financing.

2.5.1 Do community banks increase the likelihood of small businesses lending?

In this section I describe the method and the results of estimating the effect on firms' probability of having long term loan financing depending on the community bank market share in an area. The model includes control variables important for both the supply and demand side of credit. Some of them influence both supply and demand. Supply side variables are variables typically relevant in banks' and other credit institutions' screening processes, and thus important for whether a firm is granted loan financing. Demand side variables are variables which influence the firm's need for loan financing from a credit institution. The variables I control for are typically public information. Thus, the remaining differences between firms with community bank financing and other types of financing are likely to be due to private signals of soft information for which I hypothesize that community banks have an advantage.

In my empirical approach I estimate the following equation:

$$
\begin{aligned}
prob(LOAN_i = 1) = \beta_0 + \beta_1 * MarketShare_{k,s} + \beta_2 * ln(EMP_i) + \beta_3 * ln(EMP_i)^2 \\
+\beta_4 * ln(SALES_i) + \beta_5 * ln(SECURITY_i) + \beta_6 * OM_i \\
+\beta_7 * ln(AltCredit_i) + \beta_8 * FirmAge_i + \beta_9 * IND_i \\
+\beta_{10} * CENT_k + \beta_{11} * NewsSub_k + u_i,
\end{aligned}
\tag{2.1}
$$

where $prob(LOAN_i)$ is the probability of firm i having long term financing from a credit institution, while $LOAN_i$ is a dummy variable equal to one if the firm has long term credit financing, and zero otherwise. $MarketShare_{k,s}$ is the community bank market share in municipality k for firms of size category s. Thus, β_1 is the coefficient of main interest. The community bank market share is constructed by dividing the number of firm loans granted by a community bank in the municipality by the total number of loans granted in the municipality.

I control for several firm and municipality characteristics. EMP_i is firm i's number of employees. In the regression it enters in logarithmic form, as all other variables with ln in front of them in the equation. Number of employees is a proxy for firm size. I expect larger firms to be more likely to have credit financing, at least until a certain size. By including the squared value of log-employees in the model, I allow for that the largest firms are likely to be independent of financing from credit institutions. $SALES_i$ is firm i's sales. Firm sales is a proxy for the firm's ability to handle loan payments, and thus an important factor for receiving credit financing. $SECURITY_i$ includes firm i's current assets and real estate. The amount of assets suitable as collateral security can be a sorting criterion in the process of being granted credit financing (Bester, 1985). OM_i is the operating margin of firm i. Operating margin is a proxy for the firm's need for external finance. According to the "pecking order theory" firms will first try to finance projects through operating profits, then credit finance, before they resort to external equity investors. Thus, if firms have high operating margins I expect that they are less likely to have credit financing. FIN_i measures the extent of other sources of long term credit applied by firm i, such as convertible loans, subordinated loan capital, loans to mother company or industry bonds. Access to alternative sources of capital is likely to influence the demand for long term loan financing from a credit institution. $FirmAge_i$ is the number of years since establishment of firm i. In the regression, firms are split into four dummy age groups. Firm age is a proxy for the level of available documentation regarding the firm's ability to handle debt obligations. IND_i are dummies for the industry affiliation of firm i at the 2-digit NACE level. Industry affiliation can tell us about the firm's need for financing as well as the ability to handle a loan. $CENT_k$ are dummies for the geographical location of municipality k where firm i is located along a centre-periphery dimension from one to five, where one is the most central and five the most peripheral. $NewsSub_k$ is the average number of newspaper subscriptions per household in the municipality where the firm is located. Using newspaper subscriptions as one of their measures, Ostergaard et al. (2009) find that social capital increases the probability of community bank survival. Thus, community banks are on average more likely to be located in areas with higher social capital. I control for social capital as an explanatory factor for demand and supply of community bank credit.

The critique from Berger and Udell (2006), that the lending technologies applied by the banks usually are not identified in studies of small business credit availability, is partly valid also for this study. Although I have included variables such as firm assets available for collateral and other information typically relevant in a small business credit scoring, I have not been able to control for firm owner assets outside the firm's balance or whether firms are leasing instead of loaning. This follows from leasing being categorized together with other operating expenses in the firms' accounts. With regards to collateral in assets outside the firm's balance, about 7% of loans to non-financial Norwegian firms had collateral in the owners' private homes at year end 2011. If community banks are more likely to take collateral in private homes compared to other banks, then this is a source of bias in my results. I have, however, no ex ante reason to believe that community banks have a higher propensity to take collateral in private homes compared to larger banks. As far as leasing is concerned, Berger and Black (2011) find that larger banks have an advantage with regards to leasing relative to other fixed-asset lending technologies. According to year end 2011-data from Statistics Norway, non-financial firms leased assets for NOK 39 billion, while total loans to non-financial firms amounted to NOK 1 113 billion. Hence, including leased capital in the analysis is not likely to alter the total picture as it amounts to a small share of firm financing compared to loan financing.

I estimate the model parameters using a probit regression model. I expect the probability of having a long term loan to increase with the community bank market share in a municipality. The motivation is that the adverse selection problem is decreasing with better informed creditors. The results are displayed in Table 2.1. All point estimates should be interpreted as marginal probabilities of having loan financing evaluated at the mean of the independent variables. Column 1 represents the baseline regression on the full sample. In Column 2 I test the model on the sub sample of firms not affiliated with a mother company or a subsidiary, while in Column 3 I analyse the sub sample of firms with a single personal majority owner. The latter specification enables us to control for owner age and whether the firm owner has been involved in a bankruptcy in the same municipality the previous two years. These are firm owner characteristics which can give the bank valuable information with regards to the owner's ability to handle debts, and thus a potentially important part of a bank's credit screening process. In this regression I control for owner age partly because I expect that it can be harder for older owners to gain credit and partly because older owners may demand less credit due to a better private financial situation or due to higher risk aversion and focus on maintenance rather than growth.

Column 1 in Table 2.1 shows that the probability of firms having a loan increases with the community bank market share. The effect of the size of the community bank market share on the probability of loan financing is larger for the larger firms. The coefficients are statistically significant at the 1% level. Performing a Wald test I find that the effect of the community bank market share on the probability of having long term credit financing for firms with 21–50 employees is statistically significant larger at the 10% level compared to firms with 1–10 and 11–20 employees.

The community bank market share can only take on values between 0 and 1. Thus, the point estimates should be interpreted as the effect on a firm being located in a municipality where all loans are provided by the community bank compared to a municipality where none of the loans are provided by a community bank. For example, in Table 2.1 the estimated coefficient is 0.08 for the community bank market share for firms with 1–10 employees. Thus, everything equal, the probability of having a loan is eight percentage points higher in a municipality with a community bank market share of 1 compared with a municipality with a community bank market share of 0. From Table A.1 we see that 27% of the firms with 1–10 employees have long term loan financing. Hence, going from a municipality with no community bank loans to a municipality with only community bank credit would increase the share of firms with 1–10 employees having long term financing with about 30%. However, a marginal change in the community bank market share has little effect on the probability of a firm having long term financing. For example, if the community bank market share for firms with 1–10 employees increases with one percentage point, we expect the probability of having long term loan financing to increase with 0.3% on average.

From Column 1 we also see that the control variables have coefficient estimates which are in accordance with our ex-ante predictions; larger and older firms as well as firms with more assets available for collateral are more likely to have credit financing, while firms with alternative credit finance and high operating margins are less likely to demand a long term loan from a credit institution. The squared value of log-employment is also negative, which means that the probability of having long term loan financing is increasing at a decreasing rate with firm size. I also find a positive statistically significant effect at the 10% level from increasing the average number of newspaper subscriptions on the probability of having long term credit financing. This suggests that firms located in areas with higher social capital are more likely to have long term credit financing. The result seems reasonable taking into account that Ostergaard et al. (2009) find that savings banks located in areas with high social capital charge lower interest rates and face lower debt default rates.

Column 2 presents the estimation of the equation on the sub sample of firms without subsidiaries or mother companies. Again we observe that the community bank market share has a positive and statistically significant impact on the probability of having loan financing. The results from the regression on the sub sample displayed in Column 2 are very similar to the results from the full sample displayed in Column 1. This indicates that the full sample data set is not plagued with measurement errors. In Column 3 the equation is estimated on a sample of firms with a single personal majority owner. The results are still robust. In fact, a simple Wald test tells us that the coefficients estimates of community bank market share for firms with 1–10, 11–20 and 21–50 employees are not statistically different between the regressions.

In Section 2.3 I argued why there is little reason to expect today's community banks to be a selection of credit institutions located in areas with a higher demand for credit compared to other banks. Still, it could be the case that the market share of community banks is exceptionally low in municipalities were there are only a handful of firms with a demand for long term credit. These municipalities are less likely to have a branch office, and the firms are consequently more likely to be served by a national level or a larger regional bank using transaction lending technologies. Thus, it could be that these

Table 2.1:
Community banks' effect on the probability of having loan financing from a credit institution.

	(1) Full sample Coef./SE	(2) Excl. subsidiaries Coef./SE	(3) Personal majority Coef./SE
MarketShare (1–10 emp.)	.081***	.086***	.080***
	(.02)	(.02)	(.02)
MarketShare (11–20 emp.)	.089***	.075**	.074**
	(.03)	(.04)	(.04)
MarketShare (21–50 emp.)	.150***	.173***	.169**
	(.04)	(.05)	(.07)
ln(Employees)	.070***	.051***	.080***
	(.01)	(.01)	(.01)
ln(Employees)^2	-.018***	-.014***	-.021***
	(.00)	(.00)	(.00)
ln(SecurityAssets)	.036***	.037***	.023***
	(.00)	(.00)	(.00)
ln(Sales)	.014***	.033***	.035***
	(.00)	(.00)	(.00)
FirmAge (6–10)	.023***	.017***	.024***
	(.01)	(.01)	(.01)
FirmAge (11-20)	.016**	.002	.017**
	(.01)	(.01)	(.01)
FirmAge (>20)	.001	-.020*	-.006
	(.01)	(.01)	(.01)
ln(AltCredit)	-.006***	-.009***	-.001
	(.00)	(.00)	(.00)
OperatingMargin	-.022***	-.053***	-.053***
	(.01)	(.01)	(.01)
NewspaperSubscription	.044*	.034	.029
	(.02)	(.02)	(.02)
OwnerBankruptcy			.034
			(.07)
OwnerAge	NO	NO	YES
Industry (2-digit NACE)	YES	YES	YES
Centrality (1-5)	YES	YES	YES
Log-likelihood	-50426	-33440	-25903
Chi-Square	22365	13268	11590
No. of obs.	92,151	61,938	46,083

Note: This table reports the marginal effects at means from estimating a probit model on a 2011-cross section data set. The model is described in Equation 2.1. The dependent variable is a dummy variable equal to 1 if firm has long term financing from a credit institution. The explanatory variable of main interest is the community bank market share (MarketShare) for different firm sizes. Variables are defined in Table A.10. Column 1 is based on the full sample of firms, Column 2 excludes all firms part of a group of companies, while Column 3 includes only firms with a single majority owner. Cluster robust standard errors (SE) at the municipality level are reported in parentheses: * significance at ten, ** five, *** one percent.

municipalities drive my result. I approach this possibility by taking advantage of the fact that community banks have their largest market shares in rural municipalities although not in the most peripheral ones. In the regression analysis I control for the centrality of the municipality by using a centrality index ranging from 1 to 5. By excluding the most peripheral municipalities, 65 out of a total of 428, I get an indication whether the results are driven by the most peripheral municipalities where we expect both the community bank market share and the credit demand to be low. Table A.4 in the appendix shows that the results are very robust when excluding the most peripheral municipalities from the regression. A similar analysis, excluding the 55 municipalities without a physical branch office, also gives very similar results. The latter regression analysis is not displayed due to brevity.

2.5.2 Do community banks provide more credit financing?

In this section I investigate whether community banks — ceteris paribus — provide more credit than other banks. The sample is limited to firms that have long term loans from a credit institution, either a community bank or some other type of credit institution.

Due to aggregation at the municipality level of the source of credit I cannot identify the source of a specific firm's loan. Thus, I do not explicitly know whether the loan is granted from a community bank or any other type of bank. If the community bank market share is either 1 or 0 I would know for sure whether the credit was granted by the community bank or not. But only focusing on this sub sample would leave us with very few observations. Hence, as in the previous section, I use community bank market share as an indicator for the probability that the firm received credit from a community bank. The higher the community bank market share the more likely it is that the credit financing is from a community bank.

I estimate the following equation;

$$ln(LOAN_i) = \beta_0 + \beta_1 * MarketShare_{k,s} + \beta_2 * CONTROLS + u_i \qquad (2.2)$$

where $ln(LOAN_i)$ is the log transformed amount of long term loan of firm i from a credit institution, while $MarketShare_{k,s}$ is the community bank market share in municipality k for firms of size s. The control variables are the same as described in Section 2.5.1.

Table 2.2 displays the results from the estimation of equation 2.2 using OLS. All standard errors are cluster robust at the municipality level which controls for the possibility that firm level observations within the same municipality are correlated because they are selected by the same bank. As in the previous section the columns represent the equation estimated on three different samples.

From Column 1 we see that the community bank market shares for firms with 1–10 and 11–20 employees are positive and statistically significant at the 1% level, while the community bank market share effect on the firms with 21–50 employees is statistically significant at the 10% level. That is, controlled for a variety of factors, the amount of credit provided is larger if community banks have a larger share of the market in the municipality. Although the largest estimated effect is for firms with 11–20 employees, a simple Wald test finds that this estimate is not significantly different within a 95% confidence interval from the other community bank market share coefficients.

Some of the estimated coefficients of the control variables are different from Table 2.1 in Section 2.5.1. One must however keep in mind that the estimates are based on a different dependent variable and different samples. Unlike in Table 2.1, where I estimated the probability of having long term loan financing on a sample of firms with and without long term loans, the samples in the regressions displayed in Table 2.2 are all contingent on having long term financing from a credit institution. For example, from Column 1 in Table 2.2 we see that sales are negatively associated with the amount of credit provided. While, in Table 2.1, sales were positively associated with the probability of having long term loan financing. Thus, a certain level of sales is important for being considered eligible for long term credit financing (the extensive margin), while given that the firm has long term financing, the larger the sales the less is the need for credit financing (the intensive margin). Similarly, I see that the point estimates on operating margins are significantly negative for the amount of credit financing, suggesting that more profitable firms are more able to finance themselves. As expected, firms with more assets potentially available as security have more credit financing, while surprisingly I find that the amount of long term loans is positively associated with the use of alternative sources of credit. This suggests that different sources of credit are complements rather than substitutes. I also observe that firms that have existed for five years or less have more credit than other firms, while firms older than five years have the same amount of credit independently of age. This seems like a plausible result keeping in mind that the results are contingent on firms that have credit financing. While the youngest firms on average are less likely to receive loan financing, the younger firms that are granted loans from a credit institution are likely to need more capital than older more established firms.

Column 2 displays the estimation of the same equation on the sub sample of firms without subsidiaries or mother companies. The results are similar to the results based on the full sample in Column 1. Column 3 displays the results on the sample of firms with a single personal majority owner. Again I find a positive effect on the amount of credit financing from community banks. The point estimates from community bank market share are very similar to those I found for the full sample, see Column 1. The effect is, however, not statistically significant at the 10% level for firms with 21–50 employees.

In the regressions presented in Table 2.2 I did not control for any potential sample selection bias. The samples in Table 2.2 are truncated in the sense that firms which do not have long term credit are excluded. On one hand one can argue that it is not important to control for selection bias as I am interested in the effect on the selected group of firms which actually did receive loans. On the other hand, if the sample of firms that receive credit financing from community banks is systematically different from those that receive credit financing from other credit institutions then it is relevant to control for this. Table 2.1 showed that firms located in areas where community banks have a high market share have a higher probability of receiving long term credit financing. This result suggests that community banks pick up firms which other banks do not find sufficiently attractive. Thus, if there is a selection bias in the regressions on the effect of the amount of credit provided it is likely that the less transparent firms would receive less credit financing. Hence, the bias is against the results I find in Table 2.2. If anything I should expect the amount of long term financing to be even larger if I control for the sample selection bias.

I address the potential sample selection bias by applying a two-step Heckman correction. The results are displayed in Table A.5 in the appendix. The table shows that the community bank market share is estimated to have a much larger effect on the amount of credit financing when controlling for selection bias. The community bank market share coefficients for different firm sizes are all statistically significant at the 1% level. The reason why the coefficients increase when controlling for sample selection bias is likely because community banks provide credit to firms to which other banks would not have given credit at all (the extensive margin of credit). That the lambda coefficient, the inverse Mills' ratio, is statistically significant tells us that the selected group of firms which received loan financing is different from the group of firms which did not receive loan financing. The positive sign of the coefficient tells us that the factors which affect the probability of receiving long term credit financing also affect how much loan the firms get.

Moreover, similar to the analysis in Section 2.5.1, I address the potential problem of reverse causality. That is, the possibility that community banks are located in municipalities where firms demand more credit, rather than that community banks provide more credit everything else equal. As before I approach this question by excluding the most peripheral municipalities from the sample. I do this for the analysis both with and

Table 2.2:
Community banks' effect on the amount of credit financing.

	(1) Full sample Coef./SE	(2) Excl. subsidiaries Coef./SE	(3) Personal majority Coef./SE
MarketShare (1–10 emp.)	.212***	.261***	.224***
	(.04)	(.05)	(.05)
MarketShare (11–20 emp.)	.333***	.449***	.447***
	(.08)	(.11)	(.11)
MarketShare (21–50 emp.)	.232*	.409**	.258
	(.13)	(.19)	(.23)
ln(Employees)	-.316***	-.325***	-.242***
	(.02)	(.03)	(.03)
ln(Employees)^2	.074***	.090***	.067***
	(.01)	(.01)	(.01)
ln(security assets)	.804***	.747***	.751***
	(.01)	(.02)	(.02)
ln(sales)	-.059***	-.035	-.080***
	(.01)	(.02)	(.02)
Firm age (6–10)	-.147***	-.098***	-.132***
	(.02)	(.03)	(.03)
Firm age (11–20)	-.156***	-.125***	-.093***
	(.02)	(.03)	(.03)
Firm age (>20)	-.141***	-.125***	-.066**
	(.02)	(.02)	(.03)
ln(alt. non-equity finance)	.029***	.029**	.020*
	(.01)	(.01)	(.01)
Operating margin	-.356***	-.296***	-.358***
	(.03)	(.04)	(.04)
NewspaperSubscription	.101*	.123**	.158***
	(.05)	(.06)	(.06)
OwnerBankruptcy			.076
			(.23)
OwnerAge	NO	NO	YES
Industry (A-V)	YES	YES	YES
Centrality (1-5)	YES	YES	YES
F-value	759.1	505	189.2
R-squared	.5081	.4932	.3908
No. of obs.	27,802	18,979	14,435

Note: This table reports the OLS-estimates on a cross section data set of firms with long term loans from a credit institution per year end 2011. The model is described in Equation 2.2. The dependent variable is the log transformed long term loan of firm i from a credit institution. The explanatory variable of main interest is the community bank market share (MarketShare) for different firm sizes. The regressions displayed in the table are done on three different samples. See Table 2.1 for description of the samples represented in the regressions in Column 1-3. All variables are defined in Table A.10 in the appendix. Cluster robust standard errors (SE) at the municipality level are reported in parentheses: * significance at ten, ** five, *** one percent.

without controlling for sample selection bias. Excluding the most peripheral municipalities I find that the results are very similar to the results displayed in Table 2.2 and Table A.5 with only marginal changes in the coefficient estimates. For brevity's sake I only comment on the results without including the tables.

Increased competition in the banking sector is also likely to give similar results – increased probability of small credit financing, as well as increased amounts of credit – as we observed in Table 2.1 and Table 2.2. There is, however, no good reason why one should expect the community bank market share to be positively correlated with the intensity of banking competition in the market. The number of different banks that have branch offices in a municipality can be regarded as a crude proxy for the level of competition. Running a correlation analysis between the number of banks with offices in a municipality and the community bank market share, I find a small and insignificant correlation coefficient of -0.06.

However, having two banks in a small municipality is likely to provide better competition than two banks in a large municipality. In order to test for this, I run a regression with the number of banks in the municipality as the dependent variable and the number of inhabitants in the municipality as explanatory variable. This model has high explanatory power with an R-squared of 0.94. Using the predicted number of banks from the model I calculate a competition intensity coefficient by dividing the actual number of banks in the municipality by the model's predicted number of banks. If the coefficient is larger than one then the competition is higher than what one would expect based on the number of inhabitants, and vice versa if the coefficient is less than one.

I find a statistically significant correlation of 0.17 between the competition intensity coefficient and the community bank market share in the municipality. Thus, the analysis suggests that there is a small positive correlation between the community bank market share and the level of competition. I then run a sensitivity analysis on the correlation coefficient increasing the minimum community bank market share of the sample in steps of 10% starting with a minimum level of zero and gradually increasing it up to 100%. From this I find that the correlation coefficient is no longer statistically significant in municipalities where the community bank market share is larger than 30%. Moreover, it becomes negative and close to statistically significant for community bank market shares above 60%. I conclude from this that increased competition in the banking market is not likely to drive my results.

2.5.3 How do firms with community bank financing perform?

In Section 2.5.1 we saw that the probability of having credit financing increases with the share of community bank loans granted in the municipality. Moreover, in Section 2.5.2, we saw that the size of credit granted is larger for municipalities with a higher community bank market share.

If I find that community bank financed firms perform on the same level as firms with financing from other credit institutions, then this would further strengthen the hypothesis that community banks are more informed and better at detecting firms eligible for credit financing. On the other hand, if it turns out that firms with community bank financing on average perform more poorly, then this would suggest that community banks only provide more credit, taking on more risk without any advantage with respect to private information.

I measure firm performance by survival, growth and profitability. For firms with debt obligations it is also relevant whether they have the ability to handle them. Comparing the performance of firms with community bank financing with firms receiving credit from other sources will give an indication of the quality of the banks' information set in the screening process. One might expect that firms with community bank loans on average show poorer growth performance than firms with loans from other credit institutions. The rationale is that less informed banks operate with a higher threshold for granting credit, and thus one should expect their portfolios to perform better on average with respect to growth. Better informed banks on the other hand can grant credit to marginally weaker firms which are still sufficiently stable to maintain their debt obligations. Thus, I expect the portfolio of firms with community bank credit not to have a higher credit risk.

I do not have data on firm debt defaults. Instead I use inactivity, operating deficit and bankruptcy as proxies for whether firms are able to handle their debts. Survival is measured by whether a firm is active in a given year. If the firm does not have either sales or labor costs in this or the previous year, I consider the firm to be inactive. Survival is also an important measure as differences in inactivity between groups tells us whether the results are likely to be plagued by survival bias. I also investigate the probability of going bankrupt. Bankruptcy is an interesting measure as it is associated with creditors taking control, and very unlikely to be 'voluntary'. If there are more firms with community bank financing which go bankrupt, then this suggests that community banks take on more risk. I also compare the share of firms running operational deficits. This gives an indication on whether any group of firms is less likely to be able to handle their debt obligations.

To assess growth I measure the firm's development in sales, value added, number of employees and amount of debt financing. Foreman-Peck (2013) argues that sales is a particularly relevant outcome variable as it is closely related to the surplus measures of well-being from welfare economics: Consumers' surplus and firms' profits. Moreover, Norrman and Bager-Sjögren (2010) argue that sales is a proxy for customer satisfaction and the firm's ability to commercialize the product. Value added is a measure which includes both the return to the owners, the employees, the government (through taxes) and creditors. Thus, it is a measure that comprises the return to all the firm's stakeholders. Employment is a measure of the firm's ability to attract resources which in turn is a signal of the quality of the project. I also include growth in debt. Debt growth is a measure of the creditors' confidence in the firm. If one group of firms has a higher debt growth then this is likely an indication that this group of firms has creditors which are pleased with their customers. All growth measures are log transformed in the regression. To avoid negative values and to limit the most extreme growth figures for the smallest firms I add one million Norwegian kroner to all variables before taking logs. All prices are deflated with the consumer price index.

Firm profitability is measured by operating margins. Operating margins can vary considerably between industries, but this is controlled for by including industry dummies. Moreover, I limit extreme values of operating margins by winzorising them at the top and bottom 2.5 percentiles. Winzorising at the bottom 2.5 percentile means that all observations below the 2.5 percentile are set equal to the 2.5 percentile.

For the purpose of the analysis I construct a sample of firms which received long term loan financing for the first time in the period 2004–2008. Ideally I would like to identify exactly which firms received credit from a community bank and which firms received credit from other types of banks. The bank connection of the specific firm is unfortunately not identified in my data set. But I do know the share of loans granted in a municipality which stems from a specific type of bank. Thus, my approach is to assume that any firm located in a municipality with a community bank market share of 0.8 or more received credit financing from a community bank. Similarly, I set the upper community bank market share limit at 0.2 for assuming that a firm received loan financing from a non-community bank. The remaining firms, located in municipalities with a community bank market share in the interval 0.2 to 0.8, are excluded from the sample. The community bank market share levels are based on 2006-data.

Table A.6 and Table A.7 in the appendix display the descriptive statistics for the sample of firms with community bank financing (located in municipalities with a community bank market share ≥ 0.8) and the firms with non-community bank loan financing (located in municipalities with community bank market share ≤ 0.2), respectively. I see from these tables that in the treatment group the average community bank market share is 0.86. Thus, if the community banks' share of new loans is the same as the average market share in the municipality, then the measurement error is 14%. The average community bank market share is 0.07 in the control group. Thus, for the control group the measurement error is 7%.

Comparing Table A.6 and Table A.7 we see that the firms in the treatment group are smaller on average than in the control group with respect to number of employees, sales and loan size. The differences between the samples are, however, not large and the pre-treatment size variables are controlled for in the regression. From the tables we see that the community bank portfolio firms are located in municipalities where people on average subscribe to more newspapers. This suggests that the community bank portfolio firms are located in municipalities with higher social capital. We also control for this in the regression. The variables are measured one year before treatment, the only exemption is the average number of newspaper subscriptions where the firm is located which is measured at 2011. Comparing with the descriptive statistics in Ostergaard et al. (2009) the average number of newspaper subscriptions does not seem to have change much during this time period.

From the tables we also see that the community bank financed firms are less centrally located than the control group. This is as expected as community banks have their strongest positions outside urban areas. This is also controlled for in the regressions. The average credit rating before receiving credit financing was somewhat poorer for the community bank portfolio than it was for firms with loans from other credit institutions, but the difference is small relative to the standard deviations. Measured by operating return on assets (OROA) and operating margins I see that the treated and the control group had similar levels of profitability pre-treatment. About 1% of the firms are bankrupt within four years after they received loan financing. This is equal across the groups. The share of the firms which are inactive after four years and the share of firms which have had operational deficits in one or more years after the loan was granted are also similar across the groups.

I perform a differences-in-differences panel regression comparing the firms with community bank financing with the control group of firms with loans from other credit institutions. The equation estimated is the following:

$$\begin{aligned} Performance_{i,t} = \beta_0 + \beta_1 * Treated_i + \beta_2 * After_{i,t} + \beta_3 * Treated_i * After_{i,t} \\ + \beta_4 * CONTROLS_i + u_{i,t} \end{aligned} \tag{2.3}$$

where the left hand side variable $Performance_{i,t}$ varies depending on the application for firm i at time t. On the right hand side of the equation; β_0 is a constant, β_1

measures the pre-treatment difference between treated and controls, β_2 measures the common post-treatment development of the treated and the control group, β_3 is the post-treatment difference between firms with community bank financing and alternative long term financing (double difference). β_3 is the coefficient of main interest. β_4 is a vector of estimated coefficients for the control variables. The control variables include the log of the debtor firm's sales the year before treatment, log-labor costs the year before treatment, firm geography/centrality, industry (A-V), firm size, year of treatment, firm age and the average number of newspaper subscriptions in the municipality where the firm is located.

The results from the regression analyses are displayed in Table 2.3. The results displayed in Column 1–3 are estimated with a probit model, while the remaining results are estimated with OLS. The data set is a panel of the period 2002–2012 covering 2 years before and 4 years after the treatment year, i.e. the year the firm received credit. The exemption here is Column 1 and Column 2 where we only look at post-treatment data. The reason for not including pre-treatment observations here is that no firms are inactive or bankrupt prior to receiving loan financing.

In order for differences-in-differences estimates to be unbiased the treated and control groups must be on parallel-trends had they not received treatment. I cannot test this explicitly. However, running a regression comparing pre-treatment growth from t-2 to t-1 I do not find statistically significant differences for any of the dependent variables. This substantiates the assumption of parallel trends.

We see from Table 2.3 that the only statistically significant pre-treatment difference (see variable "Treated") between the firms with community bank financing and the firms with debt financing from alternative credit institutions is with respect to the share of firms running with operational deficits before receiving loan financing. The firms with community bank financing are on average more likely than the control group to run with operational deficits before receiving long term loan financing. An alternative regression model splitting the pre- and post-treatment estimates into more detailed time periods reveals that the pre-treatment differences are statistically significant two years before treatment, but not one year before treatment. Thus there are no statistically significant pre-treatment differences the year before the firms received loan financing.

Column 1 Table 2.3 compares the share of community bank portfolio firms becoming inactive in the four year period after receiving their first loan with the share of firms with financing from other credit institutions. A firm is categorized as active if it had sales or labor costs at least one of the previous two years. I see from the table that the coefficient measuring the difference between the treatment and control group with respect to becoming inactive after treatment, see variable "Treated*After", is small and insignificant. Since there are no differences with respect to becoming inactive, the remaining results are not caused by survival bias.

From Column 2 we see that there are no statistically significant differences between the community bank portfolio and the control group with respect to going bankrupt in the four year period after the loan was granted. From Column 3 we see that after the loan is provided there is a common trend of more operational deficits after the loan is provided compared to the two year period before the loan is granted. Still, I find no statistically significant post-treatment differences with respect to running with operational deficits in the period after receiving loan financing. The results in Column 1 - Column 3 all suggest that community banks do not finance firms with a higher credit risk than other credit institutions.

With respect to the growth variables sales, value added, labor costs and employees, we see that there is a strong common growth in the period after the loan is provided. This suggests that credit financing in general is positively associated with firm growth. The results indicate, however, that the growth in value added is significantly weaker at the 1% level for the firms with community bank financing. I find no statistically significant post-treatment differences in sales or number of employees. From Column 8 we see that there is a statistically significant decline in operating margins (OM) for both groups after the loan is provided. Hence, the firms do not seem able to reap economies of scale from the increased sales. By construction I also find a significant increase in long term debts from credit institutions after the loan is provided; there are, however, no statistically significant differences between the groups.

In my sample of firms with community bank financing and non-community banking there are measurement errors. As a robustness test I run the same regressions as displayed in Table 2.3 where the sample is selected based on more restrictive criteria with respect to being categorized as a firm with community bank financing or a firm credit financing from a larger bank. I increase the minimum community bank market share from 0.8 to 0.9 for a firm to be categorized as a firm with community bank credit, and similarly I decrease the minimum community bank market share criterion from 0.2 to 0.1 to be categorized as a firm with credit financing from larger credit institutions. Doing this, the measurement error is cut in half for both treated and controls. The sample size is, however, also reduced considerably. For the firms with community bank financing the sample is reduced to 38 firms, down from 204, while the control group is reduced from 8 393 to 5 894. Still, Table A.8 shows that the results are remarkably robust compared to the results presented in Table A.8. The robustness of the results indicates that the measurement error does not have a qualitative impact on the results.

TABLE 2.3:
Activity, growth and profitability for firms with community bank credit versus firms with alternative long term credit.

	(1) Active Coef./SE	(2) Bankrupt Coef./SE	(3) Deficit Coef./SE	(4) ln(sales+1) Coef./SE	(5) ln(va+1) Coef./SE	(6) ln(employees+1) Coef./SE	(7) OM Coef./SE	(8) ln(Debt+1) Coef./SE
Treated			.040**	-.011	.011	-.013	.006	-.002
			(.02)	(.02)	(.02)	(.02)	(.01)	(.02)
After			.054***	.285***	.235***	.166***	-.025***	.500***
			(.01)	(.01)	(.01)	(.01)	(.00)	(.01)
Treated*After	.005	.001	-.021	-.059	-.079***	-.030	-.011	.011
	(.00)	(.00)	(.02)	(.04)	(.03)	(.05)	(.01)	(.04)
ln(Loan)	YES	YES	YES	YES	YES	YES	YES	YES
ln(Sales l.treat)	YES	YES	YES	YES	YES	YES	YES	YES
ln(LaborCosts l.treat)	YES	YES	YES	YES	YES	YES	YES	YES
YearTreatment	YES	YES	YES	YES	YES	YES	YES	YES
FirmSize	YES	YES	YES	YES	YES	YES	YES	YES
FirmAge	YES	YES	YES	YES	YES	YES	YES	YES
Industry (A-V)	YES	YES	YES	YES	YES	YES	YES	YES
Centrality (1-5)	YES	YES	YES	YES	YES	YES	YES	YES
NewspaperSubscription	YES	YES	YES	YES	YES	YES	YES	YES
Estimation method	Probit	Probit	Probit	OLS	OLS	OLS	OLS	OLS
F-value				3601.09	5721.90	2218.69	19.99	201.70
R-squared				.76	.66	.64	.04	.20
Log-likelihood	-3,409	-1,938	-25,707	-37,605	-33,494	-35,228	4,526	-41,328
Chi-Square	989	498	1,567					
N	31,932	31,452	46,334	46,332	45,870	46,312	45,582	46,334

Note: This table compares the performance of firms with credit from a community bank versus firms with credit from other credit institutions. While Column 1–2 only investigate post-treatment differences, the regressions displayed in Column 3–8 have a difference-in-differences setup. The main explanatory variable of interest is the interacted variable *Treated*After*, which is the difference in difference estimate. The sample contains small firms with 1–50 employees receiving long term credit financing for the first time during the time period 2004–2008. The treatment group includes firms located in municipalities with a community bank market share of 0.8 or more, while the control group are selected from municipalities with a community bank market share of less than 0.2. The data, a panel for the years 2002–2012, cover a period of two years before and four years after treatment. The year of treatment is excluded from the regression. All variables are defined in Table A.10 in the appendix. Cluster robust standard errors (SE) at the municipality level are reported in parentheses: * significance at ten, ** five, *** one percent.

2.6 Discussion and conclusions

I investigate the effect of community banks on small businesses' probability of being granted credit financing as well as the amount of credit financing available. My approach is to connect firm level register accounting data with the market share of community banks at the municipality level.

In the first part of the analysis I investigate a 2011-cross section data set. 2011 was a stable year in the Norwegian economy and the most up to date data available at the time of the analysis. I find that the probability and availability of credit being granted to small businesses increases with the community banks' share of business loans in the municipality. This is consistent with the finding of Petersen and Rajan (1994) that relationship banking increases the availability of credit, and with Berger et al. (2005) who find that larger banks alleviate credit constraints less effectively. My results, however, contradict the findings of Jayaratne and Wolken (1999), Berger et al. (2014) and Beck et al. (2013), who do not find support for the hypothesis that small banks have an advantage in lending to small informationally opaque firms. The results are robust controlling for a variety of firm and municipality specific factors affecting the demand and supply of credit. Moreover, based on the historical development of the Norwegian industry composition and credit market structure, I argue that my findings are not caused by reverse causality and thus that they are likely to reveal a causal relationship between community banks and the availability of small business credit.

In the second part of the paper I conduct an analysis on a panel data set covering the period 2002–2012. Based on a sample of firms which received long term loan financing for the first time during the period 2004–2008, I do not find support for the hypothesis that firms with community bank financing are more likely to go out of business or run with operating deficits compared to firms with loans from other credit institutions. This suggests that community banks do not take on more risk in their portfolio. I interpret the result that community banks provide more financing without increased risk as evidence supporting a hypothesis that community banks have an informational advantage versus larger banks in the market for financing small businesses. This indicates that community banks play an alleviating role with respect to credit market failures for small businesses.

The banking sector is faced with new capital requirement regulations following the financial crisis in 2008–09. Community banks, which are typically small, face higher administrative costs per loan associated with enforcing and following new complex rules compared to larger banks. This puts the community bank model under pressure and there are expectations of a new wave of consolidations where small banks merge into larger entities, reaping administrative economies of scale. My results suggest that when public authorities perform cost benefit analyses of imposing new bank regulation they should also take into account the potential negative impact from consolidation on the availability of credit towards small businesses.

References

Agarwal, S. and R. Hauswald (2010). Distance and private information in lending. *Review of Financial Studies 23*(7), 2757–2788.

Beck, T., A. Demirgüç-Kunt, and D. Singer (2013). Is small beautiful? Financial structure, size and access to finance. *World Development 52*, 19–33.

Benvenuti, M., L. Casolaro, S. Del Prete, and P. Mistrulli (2010). Loan officer authority and small business lending: Evidence from a survey. *Available at SSRN 1657856*.

Berger, A. N. and L. K. Black (2011). Bank size, lending technologies, and small business finance. *Journal of Banking & Finance 35*(3), 724–735.

Berger, A. N., W. Goulding, and T. Rice (2014). Do small businesses still prefer community banks? *Journal of Banking & Finance 44*, 264–278.

Berger, A. N., I. Hasan, and L. F. Klapper (2004). Further evidence on the link between finance and growth: An international analysis of community banking and economic performance. *Journal of Financial Services Research 25*(2-3), 169–202.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan, and J. C. Stein (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial economics 76*(2), 237–269.

Berger, A. N. and G. F. Udell (2002). Small business credit availability and relationship lending: The importance of bank organisational structure. *The Economic Journal 112*(477), F32–F53.

Berger, A. N. and G. F. Udell (2006). A more complete conceptual framework for SME finance. *Journal of Banking & Finance 30*(11), 2945 – 2966.

Berlin, M. and L. J. Mester (1998). On the profitability and cost of relationship lending. *Journal of Banking & Finance 22*(6), 873–897.

Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. *American Economic Review 75*(4), 850–855.

Boot, A. W. A. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation 9*(1), 7 – 25.

Canales, R. and R. Nanda (2012). A darker side to decentralized banks: Market power and credit rationing in SME lending. *Journal of Financial Economics 105*(2), 353–366.

Cotugno, M., V. Stefanelli, and G. Torluccio (2013). Relationship lending, default rate and loan portfolio quality. *Applied Financial Economics 23*(7), 573–587.

De la Torre, A., M. S. Martínez Pería, and S. L. Schmukler (2010). Bank involvement with SMEs: Beyond relationship lending. *Journal of Banking & Finance 34*(9), 2280–2293.

Dewatripont, M. and E. Maskin (1995). Credit and efficiency in centralized and decentralized economies. *Review of Economic Studies 62*(4), 541–55.

DeYoung, R., W. C. Hunter, and G. F. Udell (2004). The past, present, and probable future for community banks. *Journal of Financial Services Research 25*(2-3), 85–133.

Feldman, R., K. Heinecke, and J. Schmidt (2013). Quantifying the costs of additional regulation on community banks. Technical report, Federal Reserve Bank of Minneapolis.

Foreman-Peck, J. (2013). Effectiveness and efficiency of SME innovation policy. *Small Business Economics 41*(1), 55–70.

Hauswald, R. and R. Marquez (2006). Competition and strategic information acquisition in credit markets. *Review of Financial Studies 19*(3), 967–1000.

Herpfer, C., C. Schmidt, and A. Mjøs (2015). The causal impact of proximity on bank lending. *Available at SSRN 2587058*.

Jayaratne, J. and J. Wolken (1999). How important are small banks to small business lending? New evidence from a survey of small firms. *Journal of Banking & Finance 23*(2), 427–458.

Kim, M. and B. Vale (2001). Non-price strategic behavior: The case of bank branches. *International Journal of Industrial Organization 19*(10), 1583–1602.

Moe, T. G., J. A. Solheim, and B. Vale (2004). *The Norwegian banking crisis*. Norges Bank Oslo.

Mudd, S. (2013). Bank structure, relationship lending and small firm access to finance: A cross-country investigation. *Journal of Financial Services Research 44*(2), 149–174.

Myers, S. and N. Majluf (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics 13*(2), 187–221.

Norrman, C. and L. Bager-Sjögren (2010). Entrepreneurship policy to support new innovative ventures: Is it effective? *International Small Business Journal 28*(6), 602–619.

Ostergaard, C., I. Schindele, and B. Vale (2009). Social capital and the viability of stakeholder-oriented firms: Evidence from Norwegian savings banks. Technical report, Norges Bank.

Petersen, M. A. and R. G. Rajan (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance 49*(1), 3–37.

Petersen, M. A. and R. G. Rajan (1995). The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics 110*(2), 407–443.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *The Journal of Finance 47*(4), 1367–1400.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The Journal of Finance 45*(4), 1069–1087.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The Journal of Finance 57*(5), 1891–1921.

Stiglitz, J. E. and A. Weiss (1981). Credit rationing in markets with imperfect information. *The American economic review 71*(3), 393–410.

Svendsen, A., B. Rønning, H. A., a. Egge, P. Meinich, A. Svensen, and A. Sandmo (1972). *Studier i sparing og sparebankvesen i Norge 1922-1972.* Gyldendal norsk forlag.

Thakor, A. V. (1996). Capital requirements, monetary policy, and aggregate bank lending: Theory and empirical evidence. *The Journal of Finance 51*(1), 279–324.

Torsvik, R. M. (1999). Statistikk mot år 2000: 1990-1991 bankkrisen. Technical report, Statistics Norway.

Uchida, H., G. F. Udell, and N. Yamori (2012). Loan officers and relationship lending to SMEs. *Journal of Financial Intermediation 21*(1), 97–122.

Chapter 3

Partly risky, partly solid – performance study of public innovation loans

Abstract: In this paper I attempt to measure the ability of a Norwegian publicly subsidized loan program to identify innovative firms that are victims of market failures. I apply three alternative control groups, which all have in common that they are well-defined and address specific unobservable characteristics of the program participants. The program participants perform better on a variety of growth measures compared to the firms rejected by the program. Compared with firms that receive private credit financing, I do not find that the program participants perform better in the upper quantiles of the contingent performance distribution despite a higher risk of becoming inactive. The latter result suggests that the program does not seem to succeed in identifying a target group of firms with a sufficiently high growth potential. Thirdly, firms with innovation loans are not outperformed by venture portfolio companies with respect to sales growth. The venture portfolio companies do, however, have lower rates of inactivity as well as stronger growth in employment and assets. The latter result possibly indicates that the venture portfolio companies are more likely to succeed in the long run. The overall results indicate that the selection competency of the bureaucrats administrating the program is at level with that of private banks, and possibly also of that of venture funds. Still, in order for the program to provide the same level of welfare improvement as regular business credit provided by the private market, I find that the positive externalities from the program must be sufficiently large to compensate for the direct public subsidy element including adjustment for the social costs of public funds.

3.1 Introduction

With the financial crisis of 2008-09, policies that intend to supplement private financial markets have received renewed interest as a response to tightened bank credit lines. According to OECD (2009), government loan and credit guarantee schemes were the most frequently applied public measures to enhance SME liquidity in response to the financial crisis. Public credit programs appeal to policy makers as they give leverage to public funds, have limited up front costs, and the liabilities are contingent and pushed into the future (Honohan, 2010). This gives credit programs an advantage over grant-based schemes.

Despite the global proliferation of publicly financed loan and guarantee schemes, the documentation on the effectiveness of such policies is scarce and the results are ambiguous (Warwick and Nolan, 2014; Valentin and Wolf, 2013; Samujh et al., 2012; Beck et al., 2008).[1] Moreover, Samujh et al. (2012) document that differences in program scope and design often make it difficult to compare and generalize across countries.

As described by Curran (2000), the main challenge in evaluating small business policies is finding a proper control group. This challenge still remains to be solved, as private sector development programs rarely are designed with a component of random participation (Warwick and Nolan, 2014). As a second best approach, one can either try to find well-controlled comparisons and/or natural quasi experiments (Angrist and Pischke, 2008). There are severe methodological challenges related to sampling in non-randomized studies. Storey (1998) distinguishes between two types of sampling biases arising from selective public policy programs: 1) Self-selection bias arising from motivated firms applying to be part of the programs, and 2) the administrative bias arising from the scheme providers choosing which firms to finance.

Several effect studies of private sector development programs apply propensity score matching (PSM) to identify control groups that prior to treatment are as similar as possible to the program participants (see e.g. Oh et al. (2009), Norrman and Bager-Sjögren (2010), Uesugi et al. (2010), Foreman-Peck (2013)). The control groups selected with PSM, however, fail to address non-observable firm characteristics that are potentially important for the self-selection into the program and/or being selected by the program administrators. In this paper, I approach the problem with non-observable sources of bias by applying three different control groups which all address potential problems with this kind of sample selection biases. Takalo (2009) emphasizes that any public

[1] McKenzie (2010) speculates that one reason why finance and private sector development policies have been dominated by less formal evaluations is that financial economists are less likely to be exposed to impact evaluation methods in their graduate classes compared to for instance health, education or labor economists.

innovation policy tool should be judged on whether it yields an expected net increase in social welfare. However, most impact studies aim at measuring the counterfactual outcome— what would have happened to the firms had they not received loan financing from the public program? I also try to measure the counterfactual outcome of not receiving an innovation loan. My main focus, however, is on output measures— such as survival, profitability and growth in sales, value added and employment —applying control groups that serve as benchmarks of the alternative use of resources outside the program.

This paper presents an effect study on the performance of firms with an innovative project receiving funding from the Norwegian publicly financed and administrated direct lending program— "the innovation loan program". The first control group contains firms which applied for innovation loans but were rejected. Program rejects are a popular control group because it indirectly controls for the firms' motivation to apply, c.f. Storey's self-selection bias. If there is no administration bias, this control group measures the counterfactual outcome, had the firms not received an innovation loan. However, as long as the program participants are not randomly selected among the pool of applicants, the estimated treatment effect is likely to contain an administrative bias. Hence, this comparison can only be considered as an upper bound of the program's effect, as the projects selected by the program administrators presumably are better than those rejected on average, even after controlling for observable characteristics.

The second control group consists of firms which received loans from a private credit institution. By comparing with a group that is in demand for credit and has been screened by an external loan officer, I implicitly control for non-observable firm characteristics that otherwise could lead to self-selection and administrative biases. Such non-observable characteristics could be growth ambitions, the entrepreneur's quality, and the quality of the project. Still, the innovation loan program is designed in such a way that it attracts a group of firms which are perceived as too risky to receive credit in the private market. Thus, this source of self-selection is not controlled for by comparing with firms with private bank loans. However, since the average risk of the innovation loan portfolio compared to a regular bank portfolio is known, it is possible to draw expectations with regards to how the innovation loan portfolio firms should perform in order to be successful. In particular, as firms with private bank loans receive the same type of treatment as firms with innovation loans, i.e. credit financing, that creates a natural welfare benchmark for the innovation loan program.

A potential disadvantage of using firms which receive private bank debt as a control group is that these firms do not necessarily take on innovative projects. Thus, if innovative projects take longer time to develop and generate sales, this control group can lead to a false conclusion due to a too short post-treatment period. In order to address this potential measurement problem, I also compare the firms receiving innovation loans with firms with venture capital financing. These make up my third control group. The advantage with this control group is that venture capitalist funds invest in innovative projects. Thus, this comparison gives a benchmark regarding the time it takes before one should expect innovative projects to start generating sales and eventually surpluses.

Comparing with program rejects, I find that the program participants have a stronger post-treatment performance. This can be considered a first test with respect to whether the program is successful in improving welfare. If there had been no differences between the treated and the rejects, then this would be a strong indication that the program is redundant with respect to financing innovative projects. Comparing with firms with private market bank loans I find only weak evidence of differences in firm value added growth, despite a higher probability of becoming inactive for the program participants. Comparing with venture portfolio companies, I find no statistically significant differences with respect to the growth in sales. However, lower rates of inactivity, as well as stronger growth in employment and assets may indicate that the venture portfolio companies are more likely to succeed in the long run compared to the firms with innovation loans.

The results suggest that in order for the program to provide welfare on the same level as regular business credit, the positive knowledge spillover effects from the innovation loan projects must amount to one third of the credit provided by the program adjusted for rents and the social cost of public funds. However, there are only weak indications that the firms with innovation loans perform weaker than the venture portfolio companies. The weighted average return of early stage European venture funds is about zero over the period 1980–2013 (EVCA, 2014). While the average return was positive until the mid nineties, it has been negative for most cohorts since. This suggests that it is a difficult environment for innovative projects to succeed in general, and not only for the innovation loan program in particular. The latter raises the question whether it is at all possible to ex-ante identify welfare enhancing innovative projects with sufficient precision.

The outline of this paper is as follows: In Section 3.2 I present and discuss the mandate of the innovation loan programme, while in Section 3.3 I describe the data set and the variables included in the study. In Section 3.4 I present the empirical strategy and the results from comparing the performance of firms with innovation loans with the firms in each of the different control groups. In Section 3.5 I discuss the welfare effects of the innovation loan program, and in Section 3.6 I summarize and conclude on the results.

3.2 The innovation loan program — facts and rationale

Innovation Norway is the Norwegian government's administrator of public programs supporting innovation and development of Norwegian businesses. It has characteristics of a "one stop shop", administrating a wide range of policy programs towards both entrepreneurs and SMEs. Innovation Norway's overarching mission during the period which I analyze (2004–2012) was to: "*Promote firm and socially profitable industrial development in all geographic regions of Norway and trigger commercial opportunities in different local districts and regions through innovation and international commerce and profiling*".

In this study I focus on the innovation loan program administrated by Innovation Norway. The innovation loan program is a public lending program established based on the assumption that the level and number of innovative projects is below the socially optimal in the sense that there are imperfections in the financial market, or that there are positive externalities from innovative projects which the private capital market does not take into account when considering whether a firm is eligible for credit. By providing credit to innovative projects, the program aims to solve this problem.

The literature on private sector development policies distinguishes between entrepreneurship policy and SME policy (see e.g. Rigby and Ramlogan (2013)). While both policies seek to improve the performance and number of economic actors, entrepreneurship policy focuses on the entrepreneur while SME policy seeks to increase the competitiveness of existing firms. The target group of the innovation loan program overlaps both these two categories. Lundström et al. (2013) define entrepreneurial policy as policy measures aimed at individuals who are interested in starting a business, as well as those who are still in a starting phase procedure, defined as activities during their first three years. They define SME policy as publicly funded measures aimed at existing firms, older than three years, with up to 249 employees.

Although the maximum size of an innovation loan is set as high as 25 million Norwegian kroner (EUR 3 million), the majority of projects financed with innovation loans can be categorized as young highly innovative companies (YIC). Schneider and Veugelers (2010) argue that YICs is a subgroup of SMEs that face particular difficulties in finding credit financing for their investments. YICs typically make investments in non-tangible assets unsuitable as collateral for bank credit (Hall, 2005). Moreover, the intangible nature of investments in innovation and R&D activities makes it hard for the firm to appropriate the full benefits of the investment as they give positive knowledge spillover effects to competitors and others. The combination of potential positive externalities and severe financial constraints makes YICs a relevant target group for public policies.

The theoretical model developed by Stiglitz and Weiss (1981) describes how information asymmetries between lender and borrower lead to rationing in the credit market, because a higher interest rate leads to problems of adverse selection and moral hazard. Besanko and Thakor (1987) and Bester (1985) argue that banks use collateral as a sorting device to solve this problem. Entrepreneurs with high quality projects and low risk of default will be willing to provide collateral, while entrepreneurs with low quality projects will not be willing to risk their assets. However, entrepreneurs with high quality projects but no securities available to serve as collateral will not gain access to credit. The latter group of projects creates a justification for public intervention in credit markets.

Public credit programs are appealing to policy makers. Credit programs give leverage to public funds, they have limited up front costs, and the liabilities are contingent and pushed into the future (Honohan, 2010). This gives credit programs an advantage over grants. Public authorities can in theory operate a direct lending program or a credit guarantee scheme without appropriating funds from public budgets. Fees and interest margins can cover running administration costs and losses. Both loans and credit guarantees, however, involve credit risk, and the government may be required to allocate funds at some point in time if the program's income is not sufficient to cover the actual losses. In the case of the innovation loan program, approximately one third of the total credit portfolio is backed by equity placed in a loss fund to cover expected losses on the portfolio.

In an international context, the most common type of financial public policy measure directed towards SMEs is credit guarantees. Essentially, there is little difference in the economic realities of a public direct loan program, such as the innovation loan program, and a public credit guarantee program. Both types of schemes aim to increase lending to the private business sector by reducing the requirement for collateral compared to regular bank loans.

While credit guarantee programs trigger private credit by providing insurance to the credit institution against the risk of firm default, direct lending programs provide these loans directly. The innovation loan is partly secured with collateral for the part of the loan exceeding 2.5 million NOK (EUR 300 000). The normal situation would be that 50% of the loan is secured, the level of required collateral can however vary between 25 and 75% depending on the operational risk and the ex-ante probability of the firm defaulting on the debt. The unsecured part of the loan is analogous to a credit guarantee.

A distinct difference between a credit guarantee scheme and direct lending program is that the credit guarantee also involves a private credit institution (usually a bank). The advantage of a credit guarantee compared to a direct lending program is that it allows for the private bank to develop know-how and technologies so that it can reduce risk and transaction costs and increase profitability on SME lending (Valentin and Wolf, 2013). This is also why, according to internal guidelines, the innovation loans should preferably be granted in co-finance with other sources of credit, either provided by private banks or by other Innovation Norway programs. Analogous to a first-loss partial credit guarantee, the innovation loan will typically have lower priority than other loans. However, in a situation where the firm has limited tangible assets available for collateral, innovation loans can be provided without co-financing with other sources of credit. In practice, the majority of firms that are granted an innovation loan falls within the latter group.

At Innovation Norway, the loan officer's task is to provide loans to projects that are expected to be socially profitable.[2] In order to understand how an innovation loan is granted it is instructive to give a brief description of the application procedure. Potential applicants for programs with Innovation Norway are encouraged to contact their regional Innovation Norway office before applying to a specific program. Thus, when a firm or an entrepreneur applies for project financing, Innovation Norway has already guided the firm into applying for the program the firm or the entrepreneur is most likely to qualify for, and where there are sufficient budgets that year.

If the project is developed by a firm with a steady cash flow and assets available for collateral, the preferred financial instrument is a loan offered at regular market terms (a so called low risk loan). Alternatively the application should be rejected because the project could be financed in the private credit market on commercial terms. To some extent this group of firms is likely to self-select out of the pool of applicants as the innovation loan is offered at an interest rate which is 1–2 percentage points above the average rate of regular fully secured market loans. If the project owners have limited tangible assets available to serve as collateral and the project is sufficiently innovative in its nature, then Innovation Norway should consider to offer an innovation loan. Still, according to Innovation Norway's internal guidelines, one criterion to qualify for such a loan is whether the firm can be expected to be able to cover interest and capital payments out of its own cash flow at the latest six months after the loan has been paid out. Alternatively, if the cash flow is not likely to be sufficient, that the loan can be serviced by other means, e.g. that the owners pay interest from their own pockets. The innovation loan can amount to as much as 50% of the project's financing needs.

[2]Previous evaluations of Innovation Norway and its programs point out that there is a deficiency of explicit measurable objectives related to the individual programs (Pöyry et al., 2010; Grünfeld et al., 2013). In their internal guidelines, Innovation Norway has operationalized the definition of 'socially profitable' as projects with an annual expected nominal return on assets of 6% or more. For the purpose of this study it is less relevant how Innovation Norway has defined socially optimal projects. Rather, I argue that a more relevant benchmark is to compare the performance of the firms with alternative uses of credit.

3.3 Data and variables

3.3.1 The data

I construct a data set combining administrative records of the innovation loan program with firm level accounting information from the Norwegian Register of Company Accounts. The Register accounts for all firms that have been granted an innovation loan. I focus on firms which received innovation loans during the time period 2004 to 2009. The database includes yearly accounting and employment figures covering the period 2002 to 2012, balance sheet figures as well as firm specific information such as industry affiliation, date of establishment and geographical location. This type of large firm level database based on the same reporting standards is an advantage when searching for firm control groups.

3.3.2 Measures of firm performance

I measure firm performance by survival, growth and profitability. Survival is measured by whether a firm is active in a given year. The firm is considered to be inactive if it does not have turnover or labor costs in consecutive periods. As firms that become inactive are likely to default on their debts it is highly relevant to see whether there are differences in survival rates between the firms with loans from Innovation Norway and firms with private bank financing. Moreover, survival is also an important measure inasmuch as it tells us whether the remaining results are likely to be plagued by survival bias.

To assess growth I measure the firm's development in sales, value added, number of employees and the (book) value of firm assets. Foreman-Peck (2013) argues that sales is a particularly relevant outcome variable as it is closely related to the surplus measures of well-being from welfare economics: Consumers' surplus and firm profits. Moreover, Norrman and Bager-Sjögren (2010) argue that sales is a proxy for customer satisfaction with the project and the management's ability to commercialize the product. I also study the number of employees over time. I interpret an increase in employment as a measure of the firm's ability to attract resources, which in turn is a signal of the quality of the project. I also study growth in value added. Similar to Norrman and Bager-Sjögren (2010) I also include asset growth. Assets is the sum of equity and debt and is a measure of the firm's ability to gather resources.

Firm profitability is measured by operating return on assets (OROA). This measure is used by Bennedsen et al. (2007) and Becker and Hvide (2013). Profits is, however, generally not a suitable variable to measure the success of young firms. Rather, the most successful firms are likely to be those that go deep into the j-curve, making large investments at the same time as they are still running operational deficits, in order to grow and succeed in the future. However, if a firm is going to be a success, at some point in time it must come out of the j-curve, and one should expect to see the profitability to improve over time.

As an indicator of the firm's ability to handle its debt obligations I also study the probability of running operational deficits.

3.4 Empirical approach and estimation results

This study applies three types of control groups trying to deal with different sources of bias. First I compare the innovation loan program participants with firms which applied for the program but which were rejected, then I compare them with firms with private bank financing and finally I compare them with venture fund portfolio companies.

Innovation loans are project specific financing, while the firm is the unit of analysis. Thus, if the project is relatively small related to the firm's total activity it is hard to identify whether the performance of the firm is due to the innovation loan project or some other project within the firm. In order to handle this measurement problem I exclude firms for which the loan amounts to less than 20% of the total assets the year before the loan was paid out. In the analysis where I compare firms with innovation loans with firms with private bank loans, the same criterion applies for the control group.

Moreover, I exclude firms that were not active two years before receiving treatment from the analysis. I do this in order to be able to control for pre-treatment differences, and in particular whether the treated and controls are likely to follow the same trend growth.

3.4.1 Comparison with program rejects

The comparison with program rejects is to be considered as a first of test with respect to whether the program is successful in improving welfare. If the innovation loan program is to be considered welfare-improving, it is a necessary but not sufficient condition that it performs better than the rejects.

Program rejects is a popular control group because it indirectly controls for self-selection bias by comparing with other firms which have the motivation to conduct investment projects. However, the innovation loan program participants are not randomly selected among the pool of applicants. Rather, the administrators have a mandate to identify and finance the potentially best projects. This suggests that there is an administrative bias in this type of comparison leading to an overestimation of the treatment effect. Wallsten (2000), however, argues that program administrators have incentives to select projects with moderate risk in order to avoid negative publicity related to failures. This line of reasoning suggests an administrative bias in the opposite direction. One must, however, keep in mind that the innovation loan program is designed in such a way that it does not attract moderate risk firms that otherwise could be financed in the private credit market. The administrative bias is consequently most likely to inflate the estimated effect. The result from this comparison therefore serves as an upper bound of the program's effect on the participants.

Some firms receive innovation loans more than one time related to different projects. For these I use the first innovation loan as the treatment year. Other firms apply for innovation loans more than one time and are rejected every time. For these firms I consider the first rejection as the year of rejection. Firms that experienced both successful and unsuccessful applications are excluded from the sample.

Table 3.1 presents summary statistics on the firms which were granted innovation loans (the treated) and the firms which had their application rejected (controls). The summary statistics are based on the year before treatment. The treatment year is the same as the year the loan was granted or rejected. The sample contains 119 firms which received innovation loans and 21 rejects in the period 2004 to 2009.[3] From the table we see that the average level of sales, total assets, labor costs and employees is quite similar for those firms which receive an innovation loan and for those that had their application rejected. However, the median firm among the firms that were granted an innovation loan is larger than the median rejected firm. The median firm among the firms which were granted an innovation loan had five employees and sales of 5.2 million NOK (EUR 0.7 million) the year before receiving an innovation loan, while the median rejected firm had two employees and sales of 1.8 million NOK (EUR 0.2 million).

[3]Innovation Norway operates with three ways of rejecting a loan application: return the application, request for withdrawl, or decline. The control group only includes firms for which the application was declined. This way we are assured that the control group only contains firms that have gone through a similarly thorough screening by Innovation Norway as those that had their application accepted.

TABLE 3.1: Summary statistics: Firms with innovation loans compared to firms rejected by the program.

	Treated (119 obs.)					Control (21 obs.)				
	mean	sd	p25	p50	p75	mean	sd	p25	p50	p75
Sales	14,799	30,257	734	5,284	13,318	19,789	54,868	436	1,824	8,781
Employees	12	19	2	5	12	13	32	1	2	8
ValueAdded	4,344	10,811	-110	1,123	5,593	7,168	21,370	-508	851	5,324
TotalAssets	21,658	64,209	2,154	6,430	15,848	32,692	109,095	1,777	4,076	14,941
YearTreatment	2007.7	1.6	2007	2008	2009	2007.8	1.7	2007	2009	2009
FirmAge	9.0	6.9	4.0	7.0	12.0	8.0	5.6	4.0	6.0	10.0
InnovationLoan	2,925	3,808	1,000	2,000	3,000	0	0	0	0	0

Note: This table displays summary statistics the year before the firms had their innovation loan application accepted or rejected during the period 2004-2009. Nominal figures are in 1000 NOK. See Table B.3 for variable definitions.

I perform a differences-in-differences panel regression comparing the firms with innovation loans with the control group of firms that had their project applications rejected by the program. The equation estimated is the following:

$$\begin{aligned} Performance_{i,t} = \alpha + \beta_1 * Treated_i + \beta_2 * After_{i,t} + \beta_3 * Treated_i * After_{i,t} \\ + \beta_4 * CONTROLS_i + \epsilon_{t,i}, \end{aligned} \tag{3.1}$$

where $Performance_{i,t}$ varies depending on the application for firm i at time t, β_1 measures the pre-treatment difference between treated and controls, β_2 measures the common growth for treated and controls, β_3 is the treatment effect on the treated (double difference), β_4 is a vector of estimated coefficients for the control variables and ϵ is the error term. β_3 is our main coefficient of interest. The control variables include dummy variables for the year the loan application was accepted or rejected as well as the pre-treatment values at t-1 of log-sales, log-total assets, and log-employees. The latter variables are included to control for pre-treatment size differences.

By using a differences-in-differences model I allow for unobserved heterogeneity between treated and controls as long as this heterogeneity is time invariant. For this assumption to be fulfilled the treated and controls must be on the same trend (parallel-trend assumption). This means that there must be reason to believe that the treated and the control group would be likely to follow the same time trend without treatment. Although this assumption is hard to test explicitly, I investigate pre-treatment behavior to substantiate that the trends are the same. Running a regression comparing pre-treatment growth from t-2 to t-1, measured in log differences, I do not find statistically significant differences in pre-treatment growth patterns for treated and controls.

Table 3.2 displays the results from the differences-in-differences regression comparing firms with innovation loans and firms that were rejected by the program. I consider a window from two years before treatment to as much as eight years after being granted or rejected an innovation loan. The only exemption is the regression with *active* as the dependent variable. In this regression I only estimate post-treatment differences as the firms are all active before receiving treatment.

The estimates measure the average effects before and after treatment. The point estimates displayed in Column 1 and Column 2 are estimated based on a probit model, and should be interpreted as marginal probabilities conditional on the mean value of the independent variables. The remaining regressions are estimated with OLS. The *Treated* estimates in Table 3.2 tell us whether there are any statistically significant pre-treatment differences in levels between the groups.

The *Treated*After* estimate in Column 1 indicates that there are no differences in the probability of becoming inactive between treated and controls, and thus that there is no survival bias in the sample. The *Treated*After* estimate in Column 2 shows that there are no statistically significant differences between the groups with respect to running with operational deficits.

The estimated coefficients for *Treated*After* in Column 3–6 tell us that the firms receiving innovation loans have significantly higher growth in sales, value added, employees, and total assets compared to the rejects. We see for example that the estimated average post-treatment development in sales is 29 log-points. For relatively small changes, log-points is a good approximation for percentage points. In this case one must be careful with the interpretation since I have added a constant of two million NOK before taking logs. Thus, the percentage growth will be somewhat underestimated, in particular for the smallest firms. Still, as an approximation, in the remaining of the article I will refer to the log-points estimates as percentage points.

The table shows that there is no statistically significant common growth for treated and controls, see *After* estimates. The only exception is for employees. Here we see that there is a (weakly) statistically significant negative development. Taking into account that we do not see any positive development in assets, in addition to a negative development in employees, this suggests that the firms that do not receive innovation loan financing do not succeed in finding alternative financing at a later point in time.

This analysis shows that the firms that are granted innovation loans experience higher growth than those rejected by the program. By comparing with rejected applicants self-selection into the program is controlled for. Unfortunately, I can not separate the effect from receiving a innovation loan from the possible administrative bias stemming from the screening process by Innovation Norway's loan officers selecting the best projects. Although I perform a differences-in-differences regression controlling for certain pre-treatment characteristics, some administrative bias is likely to remain in the sample. This implies that the firms which received innovation loans would have had a better development than the firms which did not receive an innovation loan also in case none of them had received a loan. In fact, in a separate analysis attached in appendix B.1, I show that the administration at Innovation Norway is able to operate regular lending activity on the same level as private banks. Although regular bank screening and innovation project screening are not equivalent, this supports an assumption that Innovation Norway has a screening competency which enables them on average to select the better among projects.

However, if the firms with innovation loans had not received loan financing the growth would most likely also have been lower, and at least delayed. This is also supported by a survey among participants for which a vast majority report that the innovation loan program was important for the realization of their project (Grünfeld et al., 2013). The fact that the asset growth is at level with growth in sales and value added, suggests that financing is an important part of the firms' growth. Finally, I find no statistically significant differences in profitability between the groups. The latter is interesting because one could expect that the average profitability would go down when the asset volume increases. One explanation could be that the firms with innovation loans are more likely to receive other types of support such as grants, which would improve profitability.

Table B.4 in Appendix B.2 displays a regression on the same sample but replacing the aggregate before and after treatment dummies with period specific time dummies as well as the interaction of the *Treated* variable with these time dummies. The detailed time estimates are interesting because they allow for non-linearities in the development both before and after treatment, possibly revealing sub-trends not captured by the more general pre- and post-treatment variables.

The results in Table B.4 are generally very similar as displayed in Table 3.2. The estimates suggest that there is a tendency that firms with innovation loans have a higher probability of becoming inactive with time. Particularly, one should be careful about the interpretation of the estimates five to eight years after treatment as there is likely some survival bias in these estimates. Although the differences-in-differences estimates for value added post-treatment are positive, they are not statistically significant at the 10% level. There is a tendency of firms with innovation loans having weaker results than firms which do not receive innovation loans five to eight years after treatment. This is likely because many of the firms that do not receive innovation loans never really get started with their project, and that they consequently are less likely to run with operational deficits. Table B.4 can also give us information about the parallel trend assumption. The fact that the coefficients *Treated*2 years before treatment* and *Treated*1 years before treatment* are not statistically different from zero, indicates that the pre-treatment growth is about the same for firms with innovation loans and firms which had their project rejected.

TABLE 3.2: Survival, growth and profitability of firms with innovation loans compared to firms that were rejected by the program.

	(1) Active Coef./SE	(2) Deficit Coef./SE	(3) ln(sales+2) Coef./SE	(4) ln(va+2) Coef./SE	(5) ln(employees+1) Coef./SE	(6) ln(assets+2) Coef./SE	(7) OROA Coef./SE
Treated		.043	-.044	-.221	-.002	-.077	.053
		(.11)	(.08)	(.13)	(.08)	(.06)	(.07)
After		.006	-.082	-.077	-.230*	-.084	.075
		(.10)	(.11)	(.13)	(.14)	(.11)	(.08)
Treated*After	-.040	-.038	.292**	.375**	.414***	.469***	-.029
	(.04)	(.11)	(.13)	(.15)	(.15)	(.13)	(.09)
Estimation method	Probit	Probit	OLS	OLS	OLS	OLS	OLS
F-value			103.8	36.04	104	77.47	4.268
Adjusted R-squared			.7779	.5499	.7421	.7089	.0988
Log-likelihood	-207	-489	-665	-804	-736	-766	-217
Chi-Square	8	51					
No. of obs.	632	807	807	737	808	807	789

Clustered standard errors (SE) at the firm level are reported in parentheses: * significance at ten, ** five, *** one percent.

Note: This table displays differences between firms that had their innovation loan application accepted and rejected during the period 2004–2009. The regressions have a differences-in-differences setup (see Equation 3.1). The data is panel for the period 2004–2012 covering a window of two years before and until eight years after the application was accepted or rejected. The exemption is the regression in Column 1 which only estimates post-treatment differences. The year of treatment is excluded from the sample because it cannot be clearly assigned to either before or after treatment. The coefficients displayed in Column 1–2 should be interpreted as marginal probabilities at mean values, the estimates in Column 3–6 are log-points, while OROA in Column 7 estimates growth. See Table B.3 for a definition of the dependent variables. For numerical values I have added two million NOK before taking the natural logarithm, while for employees I added the number 1. In the regression I control for business cycle, log-sales at $t-1$, the squared of log-sales at $t-1$, log-employees at $t-1$, the squared of log-employees at $t-1$, log-total assets at $t-1$, the squared valued of log-total assets at $t-1$, log-loan size, and pre-treatment growth in sales and employees from $t-2$ to $t-1$.

3.4.2 Comparison with firms with private bank loans

Firms with private bank loans is a relevant comparison as both groups of firms have been granted long term loan financing related to a specific investment project. By comparing the innovation loan program participants with firms which applied and received private long term credit the same year as the treatment group, I implicitly control for a variety of unmeasurable firm characteristics important for receiving credit finance. That is, for both groups there have been external loan officers who have assessed the quality of the investment project and the firms' ability to handle future debt payments and based on this assessment decided to grant loan financing. This is an approach which reduces administrative bias between the treated and control group. Examples of characteristics available to creditors but which are not directly observable from the data I have at hand, could be qualitative information on the entrepreneur's quality and growth ambitions, or the size of contracts on future sales.

Comparing the innovation loan program participants with firms with private bank loans controls for certain aspects of self-selection, such as the motivation to undertake an investment project. Still, as explained in Section 3.2, innovation loans are offered at an interest rate which is higher than the average rate offered by private banks. The sample of firms with innovation loans is thus by design a self-selected group of firms which otherwise would not have received private bank financing. This means there is a self-selection bias with respect to the level of riskiness of the project in the sample.

Similar to many other recent effect studies of policies for private sector development, I apply the method of propensity score matching (see e.g. Oh et al. (2009), Norrman and Bager-Sjögren (2010), Uesugi et al. (2010), Foreman-Peck (2013), Ono et al. (2013)). In propensity score matching, each of the treated firms is matched with an unsupported firm selected contingently on having the same observable pre-treatment characteristics as the participating firm. Based on the matched sample it is then possible to measure the average treatment effect among the treated (ATT) by comparing with the non-treated firms. For the ATT to be observable, the propensity score matching must, however, satisfy two crucial assumptions: the conditional independence assumption (CIA) and common support (CS). For the CIA to hold we must believe that we are able to identify a twin for each of the treated firms by matching the firms based on observable characteristics. That is, had the supported firm not received finance from Innovation Norway, then the matched firms would on average have had the same development.

The assumption of common support requires that there exists a good match for the program participant within the total population of unsupported firms. In practice this is assured by matching each of the firms from the group of supported firms with one more unsupported firms with similar propensity scores. If such a firm exists in the group of unsupported firms, then the treated firm's counterfactual outcome can be estimated.

Firms tend to differ in more ways than what is measurable, If the unmeasurable differences are not randomly distributed between treated and controls, and these differences have an effect on outcome, then the estimates will remain biased. In fact, in this matching I know that the CIA is violated as the firms with innovation loans are a group of firms which is perceived as too risky to be granted private bank financing, while the control group is a group with private bank financing. The advantage, however, is that I have clear expectations on what the bias between the groups is. This enables me to make clear predictions on what type of results I would expect for the innovation loan program to be successful. The latter separates this study from most other studies applying propensity score matching exclusively on observable variables. I expect that there is more volatility in the group of firms with innovation loans compared to firms with private bank financing since the innovation loan firms are self-selected based on having higher risk. Thus, I expect firms with innovation loans to have higher default rates but also more growth successes.

When searching for matches among the population of firms with private bank financing I match with respect to a variety of standard quantitatively measurable control variables. Some of the variables are matched exactly, such as industry (NACE A-V), geography (centrality 1–4) and loan vintage. Pairing with respect to firms receiving long term loan financing the same year controls for business cycle effects. Exact matching means that I only search for matches within the same industry-region-vintage as the firm which received an innovation loan. The propensity scores are estimated based on a probit model including the following pre-treatment characteristics: log-sales, log-total assets, number of employees, firm age and log-loan size. These are potentially important characteristics when comparing the effect of credit finance on firm performance. The square of the log transformed variables and the square of the number of employees are also included in the propensity score matching. The latter is to control for possible second order effects. Moreover, in order to improve the likelihood of a common trend assumption, I also match the firms' pre-treatment growth in sales and employees in the period t-2 to t-1 before receiving loan financing.

I have a sample of 132 firms with innovation loans during the period 2004–2009 for which I try to find a match. Some firms received more than one innovation loan related to different projects during that period. I use the year of the first loan in that period as the treatment year. I apply a one-on-one nearest neighbour matching with replacement. Replacement means that the same firm may be used as a match more than one time.

From the propensity score matching, 99 of the firms found common support within a probability radius of 0.05.

Table 3.3 displays the pre-treatment statistics on the matched sample of firms with innovation loans and firms with private bank loans. The table shows that the control group is a good match with respect to quantifiable pre-treatment firm characteristics. From Column 1 and Column 2 we see that the pre-treatment mean values of sales, total assets, and number of employees are similar for the firms that received innovation loans compared with the group which received private bank loans. This is also confirmed by the t-test which fails to reject any of the mean pairs as significantly different. The size of the loan that the firms receive, measured by the size of long term credit in the firm's accounts, is higher among the controls. The difference is, however, not statistically significant between the groups. Sales, total assets, employees and loan size are not normally distributed variables. Thus, the t-test may not be a good test for comparing means. However, a plot of the distribution for treated and controls reveals that the distributions are similar for treated and controls. Due to brevity, these graphs are not displayed. Similar pre-treatment growth is essential in order to substantiate the parallel trend assumption for treated and controls. Table 3.3 shows that the mean value of pre-treatment sales and employee growth is similar among treated and controls. Running a regression comparing pre-treatment growth for all my selected performance variables for treated and controls, I find that the alternative hypothesis that the pre-treatment growth levels are different is highly insignificant. This result supports the assumption that the treated and controls are on a parallel trend.

Based on the matched sample I perform a differences-in-differences panel regression comparing firms with innovation loans with the matched control group of firms with private bank loans from the propensity score matching (PSM). This is the same model as described in Equation 3.1, the only exemption being that I also control for loan size. The control variables increase estimation efficiency by adjusting for any remaining residual bias between treated and controls. Notice that the treatment year is the year the loan was paid out, not the year the loan was granted. This is an important difference which improves the accuracy of treatment as there is usually some lag between the date when the loan was approved, and the time when the project is initiated and the loan paid out.

In the matching analysis I implicitly control for much of the systematic risk by matching with respect to industry-region-vintage cohorts as well as firm size and amount of credit financing. Thus, given that the remaining difference between treated and controls is predominantly unsystematic risk, this should according to standard financial theory imply that the required rate of return is the same for firms with innovation loans and

TABLE 3.3: Comparison of pre-treatment means of matched variables for firms with innovation loans and control group with loans from private banks.

	Mean			t-test	
Variable	(1) Treated	(2) Control	(3) %*bias*	(4) t	(5) $p \geq \|t\|$
Sales	8,858	7,429	10.2	0.7	0.484
Employees	7.8	6.7	10.1	0.69	0.489
ValueAdded	2,538	2,988	-7.8	-0.53	0.6
TotalAssets	10,443	12,817	-6.9	-0.48	0.63
Loan	3,191	4,541	-10	-0.7	0.482
SalesGrowth	0.074	0.0733	0.5	0.03	0.973
EmployeeGrowth	0.101	0.0814	7.3	0.5	0.618
FirmAge	8.2	13.6	-66.8	-4.6	0

Note: Column 1 displays the mean value of the matched variables at t-1 for the firms with innovation loans (treated). Similarly, Column 2 displays the mean value for the control group at t-1. The mean values of the nominal variables are in 1000 NOK. In the matching I use log transformed variables and the square of the log transformed variables, while the table displays the absolute values. Sales growth and employee growth are measured by differences in logs from t-2 to t-1. The %bias displayed in Column 3 is the percentage difference of the sample means in the treated and non-treated as a percentage of the square root of the average of the sample variances in the treated and non-treated groups (formulae from Rosenbaum and Rubin, 1985). Column 4 and Column 5 display the t-tests for equality of means in the two samples. The null-hypothesis is that the means are equal, thus a low p-value will reject this hypothesis.

the control group of firms with private bank loans. Assuming that firms with private credit financing have an expected return above or equal to the required return on equity, the innovation loans will be an efficient use of resources if the portfolio of firms with innovation loans is at least as successful as the firms with financing from private credit institutions.

Table 3.4 presents the regression results from comparing the firms with innovation loans with the matched group of firms with regular private bank financing. As expected we see from the *Treated* estimates that there are pre-treatment differences between the two groups with respect to the share of firms with operating deficits (Column 2), the level of valued added (Column 4), as well as the level of operating returns relative to total assets (Column 7). That is, at the time of applying for loan financing, the firms that receive innovation loans are less likely to have a sufficient cash flow to handle debt payments. This is in accordance with our expectations, as we know that firms that are granted innovation loans need only to be expected to handle debt payments within six months after the loan has been paid out to be eligible for loan financing.

The estimate in Column 1 tells us that the firms with innovation loans are significantly more likely to become inactive in the period after the loan has been paid out, see coefficient *Treated*After*. This implies that the remaining post-treatment estimates, Column 2–7, must be interpreted with caution as there is a tendency of survival bias in the sample. For example, the table shows that the firms with innovation loans have higher post-treatment growth in value added relative to the firms with private bank financing. This may, however, be because the firms which had the poorest value added, e.g. due to poor profitability, went out of business. To illustrate the potential size of the survival bias, assume that the firms that become inactive have a sales growth of -100%. We see from the table that the remaining innovation loan firms have an average sales growth of 24.3% more than the firms with private bank financing after the loan was paid out. If we take the survival bias into account, performing the following simple back of the envelope calculation (0.066*(-100)+(1-0.066)*24.3), then sales growth after treatment is still 16.1% higher for the firms with innovation loans. Given the same standard errors this estimate would have a p-value of 0.054. Thus, even when controlling for sample survival bias, the difference in value added growth is still most likely positive and statistically significant at the 10% level.

The estimates tell us that there is a statistically significant positive growth in sales and value added for both treated and controls in the period after receiving loan financing, see coefficient *After*. Employee growth is also almost statistically significant at the 10 percent level. This suggests that loan financing facilitates growth, although the analysis does not tell us what the growth would have been for these firms without credit financing. Looking at the *Treated*After* estimates it is interesting that although both groups have a statistically significant asset growth, the growth is significantly larger for firms with innovation loans. This suggest that the firms with innovation loans receive more follow up financing.

TABLE 3.4: Survival, growth and profitability of firms with innovation loans from Innovation Norway compared to firms with private bank loans: Overall performance.

	(1) Active Coef./SE	(2) Deficit Coef./SE	(3) ln(sales+2) Coef./SE	(4) log(va+2) Coef./SE	(5) ln(employees+1) Coef./SE	(6) ln(assets+2) Coef./SE	(7) OROA Coef./SE
Treated		.294***	.015	-.207***	-.000	-.011	-.267***
		(.06)	(.04)	(.07)	(.04)	(.04)	(.04)
After		.072	.118*	.100*	.088	.213***	-.059**
		(.06)	(.06)	(.06)	(.07)	(.06)	(.02)
Treated*After	-.066*	-.130*	.111	.243**	.068	.220**	.142***
	(.03)	(.07)	(.10)	(.10)	(.11)	(.11)	(.04)
Estimation method	Probit	Probit	OLS	OLS	OLS	OLS	OLS
F-value			97.66	43.99	131.3	128	6.686
Adjusted R-squared			.7372	.5177	.7546	.748	.1247
Log-likelihood	-301	-726	-954	-1,020	-991	-979	-172
Chi-Square	17	63					
No. of obs.	932	1,201	1,167	1,116	1,172	1,167	1,145

Clustered standard errors (SE) at the firm level are reported in parentheses: * significance at ten, ** five, *** one percent.
Note: The regression is based on a matched sample of firms with innovation loans and firms with private bank loans. See Table 3.2 for a detailed description of the table. The estimation model is the same as described in Equation 3.1, the only exemption being that this regression also controls for loan size.

As a robustness test I run a regression on the same sample of firms as in Table 3.4, but with a different model specification. In this model the overall *After* and *Treated*After* variables are split into more detailed time periods. The results are displayed in Table B.5 in the appendix. The more detailed time period estimates reveals that the difference in share of inactive firms increases over time. In fact, after 5–8 years the share of inactive firms is 25.8% higher. The analysis also suggests that the difference with respect to the higher share of innovation loan firms running with operational deficits is persistent also after treatment. This illustrates that many of the innovation loans firms have problems handling their debt obligations. The analysis also suggests that the firms with innovation loans have a higher sales growth than firms with private bank debt 5–8 years after treatment. However, if we take the survival bias into account (0.258*(-100)+(1-0.258)*42.7), then sales growth 5–8 years after treatment is 6%. Assuming the same standard errors, this estimate would have been highly insignificant with a p-value of 0.39. It should be noticed that the panel is not balanced in the sense that the large 2009-cohort of innovation loans only has three years of observations after receiving an innovation loan, while the 2004-vintage is the only one that has eight years. Thus, the estimates for performance after five years or more are based on the vintages of 2004–2007.

In accordance with expectations, the results presented in Table 3.4 and Table B.5 suggest that firms with innovation loans are more likely to become inactive and to run with operational deficits. Since the firms with innovation loans have a higher operational risk than firms with private bank loans, the surviving innovation loan firms should have a higher growth than the firms with private banks. In particular one should expect the distribution of firms with innovation loans to have higher growth in the upper quantiles of the distribution compared to a group of firms with regular bank loans. The regression results presented in Table 3.4 and Table B.5 provide some indication that firms with innovation loans experience higher growth in sales after five years or more, that they have a higher increase in employment after 1–2 years after treatment, and that they accumulate more assets.

To investigate whether the upper tail of the distribution is different for the treated group I follow the method of Athey and Imbens (2006) constructing a quantile difference-in-difference estimate. If the innovation loan program is successful in screening firms and their projects I expect the group of firms with innovation loans to outperform the firms with private bank loans in the right tail of the performance distribution.

There are some essential differences between the linear regression model and the quantile regression model. For the conditional mean in the linear regression model to be unbiased the error term is assumed to have an expected value of zero. In the quantile regression model the error term is required to be zero at the quantile I am interested in.[4] For example, when we look at the 0.75-quantile, we must put a restriction which says that 75% of the residuals should be negative and 25% should be positive. Thus, in a single covariate case the regression line will pass through a pair of data points where one quarter of the observations will be above the estimated regression line and three quarters will be below the regression line. There are typically multiple solutions satisfying the zero error term property. The quantile regression estimate is derived by minimizing the sum of the absolute values of the residuals, weighted according to the quantile. For example, with the 0.75th quantile the positive residuals are given larger weight (0.75), while the negative residuals are given a smaller weight (0.25) in the minimization problem.

Table 3.5 displays the results of quantile regression at the 75th, 90th, and 95th percentile of the contingent performance distribution respectively. Missing observations are given the value zero. This is because I want the quantile regressions to capture the fact that going out of business is poor performance, and not just missing variables.

Starting from the top of the table, we see that generally there are no statistically significant differences between the growth of the firms with innovation loans and private bank loans. However, measured in sales, we see that the 75th percent best firm among the firms with innovation loans has a 50% higher growth in sales after 5–8 years. The result is statistically significant at the 10% level. Moreover, 1–2 years after treatment the firm at 75th percentile have 35% higher growth in employment. This is similar to what the average performance estimates in Table B.5. With respect to OROA, we see that the 75th best firm with innovation loans have a statistically significant weaker profitability before receiving loan financing, but that the difference gradually decreases over time. 3–4 years after the loan was paid out there are no differences between the groups.

At the 90th percentile there are few significant differences between the group of firms with innovation loans and the firms with private bank loans. Most of the post-treatment coefficient estimates are in disfavor of the firms with innovation loans, although few are statistically different from zero. The exception is employment where I find a statistically significant weaker growth in employment for the firms with innovation loans. The results on OROA follow the same pattern as at the 75th percentile.

Generally, quantile regression estimates are less stable the further away the percentile is from the median. This is because a large weight in the regression is put on a few observations at the tail of the distribution. In this case the normal distribution may not be an appropriate assumption (see Chernozhukov and Fernández-Val (2011)). Still, at

[4] In the standard linear regression model the error term is also assumed to have a constant variance (homoscedasticity). In the quantile regression model the only assumption on the error term is that it is zero at the relevant quantile. For more on quantile regressions see e.g. Hao and Naiman (2007) or Khandker et al. (2010).

the 95th percentile we see the same pattern as at the 90th percentile. We have negative but statistically insignificant estimates for post-treatment growth in sales. For value added we see that there are statistically significant pre-treatment differences in levels which last until 1–2 years after treatment. For employment we see a higher growth for firms with private bank loans. At the 95th percentile of the contingent distribution, the firms with innovation loans have a statistically significant lower employment growth compared to firms with private bank loans after five years or more. Overall, the quantile regression results do not seem to support the hypothesis that the surviving firms with innovation loans outperform the group of firms with regular bank loans in the upper tail of the distribution. Thus, it does not seem as if Innovation Norway succeed in selecting a group of firms with a higher growth potential than firms with regular bank loans.

3.4.3 Comparison with venture portfolio companies

Typically, innovative projects are expected to take a longer time to develop compared to standard projects, but if they succeed they can give high returns. Thus, given that innovative projects have a different time profile with respect to development and commercialization, the comparison with projects financed with regular bank loans may falsely give the impression that the firms with innovation loans underperform although it is really an issue of timing.

Thus, as an alternative to firms with private bank financing, I also compare the firms with innovation loans with firms that received venture fund financing during the period 2004–2009. The advantage with this control group is that venture capitalist funds also invest in innovative projects. In fact, 12% of the firms with innovation loans already had private equity fund investors at the time the loan was granted by Innovation Norway. This suggests that venture portfolio companies are a relevant control group.

Table 3.6 displays summary statistics the year before receiving financing for the sample of firms with innovation loans and venture portfolio companies respectively. Firms that have received both venture fund financing and innovation loans are excluded from the sample. The reason for this is that I can not separate the effects of the two sources of capital from each other. The final sample contains 128 firms with innovation loans and 34 firms with venture fund financing. From the table we see that the average size of the venture portfolio companies is larger than that of the firms receiving innovation loans, while the size of the median firm is more similar. This implies that the sample of venture portfolio companies contains some larger firms.

Table 3.5: Firms with innovation loans compared to firms private bank loans: quantile regressions.

	(1) ln(sales+2) Coef./SE	(2) ln(va+2) Coef./SE	(3) ln(emp.+1) Coef./SE	(4) ln(assets+2) Coef./SE	(5) OROA Coef./SE
75 percentile					
Treated*2 years before treatment	.159	-.010	.357	-.017	-.191***
	(.40)	(.22)	(.26)	(.20)	(.06)
Treated*1 year before treatment	.079	-.036	.336	-.027	-.142***
	(.29)	(.17)	(.22)	(.24)	(.04)
Treated*(1-2) years after treatment	.179	-.008	.352*	.143	-.079***
	(.32)	(.17)	(.21)	(.15)	(.03)
Treated*(3-4) years after treatment	.191	.186	.219	.011	-.039
	(.59)	(.33)	(.31)	(.19)	(.03)
Treated*(5-8) years after treatment	.508*	-.032	-.000	-.212	-.032
	(.29)	(.21)	(.46)	(.47)	(.05)
R-squared	.023	.010	.022	.017	.058
No. of obs.	1292	1292	1292	1292	1292
90 percentile					
Treated*2 years before treatment	.272	.274	-.223	.123	-.205***
	(.21)	(.30)	(.23)	(.29)	(.07)
Treated*1 year before treatment	.329	.226	.065	.033	-.210***
	(.25)	(.28)	(.29)	(.40)	(.05)
Treated*(1-2) years after treatment	.194	.184	-.245	.047	-.112*
	(.21)	(.20)	(.18)	(.25)	(.07)
Treated*(3-4) years after treatment	-.125	.001	-.270	.169	-.068
	(.23)	(.16)	(.22)	(.36)	(.07)
Treated*(5-8) years after treatment	-.464	-.276	-.651*	.165	-.011
	(.53)	(.38)	(.37)	(.48)	(.06)
R-squared	.010	.001	.008	.006	.058
No. of obs.	1292	1292	1292	1292	1292
95 percentile					
Treated*2 years before treatment	.361	.382**	.260	-.059	-.070
	(.44)	(.16)	(.42)	(.38)	(.15)
Treated*1 year before treatment	.147	.276	.121	.018	-.307**
	(.21)	(.23)	(.32)	(.29)	(.13)
Treated*(1-2) years after treatment	.165	.372***	-.017	-.014	.068
	(.22)	(.14)	(.25)	(.39)	(.09)
Treated*(3-4) years after treatment	-.207	.155	-.095	-.334	-.040
	(.26)	(.18)	(.20)	(.68)	(.07)
Treated*(5-8) years after treatment	-.753	-.028	-.340*	-.065	.075
	(.54)	(.21)	(.20)	(.56)	(.13)
R-squared	.001	.003	.013	.006	.007
No. of obs.	1292	1292	1292	1292	1292

Standard errors (SE) are reported in parentheses: * significance at ten, ** five, *** one percent.
Note: The data set and the control variables are the same as in Table 3.4. The only difference is that I replace missing values with zero in order to avoid bias, e.g. due to firms falling out of the sample. In the estimation I use the program qreg2 in STATA developed by (Machado and Santos Silva, 2013). Using qreg2 the standard errors and t-statistics are asymptotically valid under heteroskedasticity and misspecification.

Table 3.6: Summary statistics: Firms with innovation loans compared to venture fund portfolio companies.

	Treated (128 obs.)					Control (34 obs.)				
	mean	sd	p25	p50	p75	mean	sd	p25	p50	p75
Sales	14,088	29,390	518	5,107	12,088	19,925	43,102	559	3,157	15,349
Employees	11	18	2	5	11	14	27	2	6	14
ValueAdded	4,206	10,359	-211	1,163	4,566	3,681	9,944	-394	1,409	6,246
TotalAssets	20,521	62,113	1,689	5,779	15,301	57,779	269,145	2,989	6,917	14,329
YearTreatment	2007.7	1.5	2007.0	2008.0	2009.0	2006.8	1.7	2005.0	2007.0	2008.0
FirmAge	8.3	6.8	3.5	6.0	10.0	9.0	6.4	4.0	7.5	12.0
InnovationLoan	2,848	3,755	900	2,000	3,100	0	0	0	0	0

Note: This table displays summary statistics the year before the firms received an innovation loan or venture fund financing during the period 2004-2009. Nominal figures are in 1000 NOK. See Table B.3 for variable definitions.

As both treated and controls are engaged in innovative projects I expect the average development and commercialization period to be similar. The time of treatment for the firms with innovation loans is measured as the year the innovation loan is paid out, while the time of treatment for the control group is when the venture fund makes its first investment in the portfolio company. I find that among the firms which received both venture financing and innovation loans the venture financing is provided on average one year before the loan. Thus, if anything, we should expect the firms with innovation loans on average to be more mature compared to the firms with venture financing.

In contrast to the comparison of firms with innovation loans with firms with private bank loans, I expect the venture backed firms to have a more volatile growth but a higher expected value than the firms with innovation loans. This hypothesis follows from the fact that firms which receive innovation loans are expected to be able to handle their debt obligations at the latest six months after the loan is paid out. Venture portfolio companies are rarely financed by debt financing and do not face the same obligations. I do, however, expect the firms with venture capital financing to go through a tighter screening process with respect to growth potential compared to the firms with innovation loans. If I find that the venture portfolio companies experience higher growth at an earlier stage than the firms with innovation loans, then this would indicate that the time span I look at— one to eight years after treatment —is sufficient to capture growth from innovative projects. If, however, there are no differences, then this suggests that the time period to measure post-treatment performance may be too short.

Table 3.7 displays the results from a regression analysis comparing firms with innovation loans with a control group of firms which received venture fund financing for the first time during the same period. The firms with venture fund financing are already a selected group of firms. Thus, I do not use propensity score matching on this sample. As before I apply a differences-in-differences model. Column 1 and Column 2 are estimated with a probit model, while the remaining are estimated using OLS. See Equation 3.1 for details on the estimation model. I study the assumption of parallel trends by running a regression comparing pre-treatment growth in my selected performance variables for treated and controls. I find that the alternative hypothesis, that the pre-treatment growth levels are different, is highly insignificant for all my performance variables. This supports the assumption that the treated and controls are on a parallel trend, and thus that the post-treatment estimates are unbiased.

From Table 3.7 Column 1 we see that the firms with innovation loans are more likely to become inactive compared to the venture portfolio companies. To some extent this is surprising as I would have expected the firms with innovation loans on average to be less risky than the firms with venture capital financing. On the other hand, the venture portfolio companies have owners with financial muscles which are able to keep the firm running for a longer period of time given that they keep their faith in the project. The estimated difference in the share of firms becoming inactive is, however, not large, and consequently the survival bias in the remaining coefficients is limited. Column 2 shows that the firms with innovation loans are less likely to run their operations with deficits. This is not surprising as venture fund portfolio companies typically increase their operational deficits when they find investors. This is part of the so called j-curve with increasing operational deficits over some time in the hope of cashing out on the investment in the end. Firms with innovation loans should on their side be able to handle their debt obligations, something which is challenging if running with operational deficits. Interestingly, in contrast to the results we saw in the comparison with firms with bank financing, there seem to be no pre-treatment differences with respect to the share of firms running with operational deficits before receiving loan financing. This suggests that the control group of venture portfolio companies has a development profile that is more similar to the firms with innovation loans compared to the firms with private bank financing.

Table 3.7 reveals a statistically significant positive growth in sales for both treated and controls after treatment of 37.4%, see coefficient *After*. I do, however, not find statistically significant differences between the two groups. Similarly, with respect to value added I find no statistically significant differences between the groups after treatment, see Column 4 *Treated*After* estimate. For employees I find a statistically significant positive development after treatment for both groups, although significantly weaker for firms with innovation loans. From Column 6 we see that both groups have a strong common growth in assets. It appears that the asset growth is weaker for the firms with innovation loans, although the difference is at the margin not statistically significant at the 10% level. We see that the firms with innovation loans are generally more profitable in terms of OROA. This is consistent with these firms being selected based on the expectation that they can handle debt obligations at the latest six months after the loan is paid out. In comparison, even successful venture backed portfolio companies typically run their operations with operating deficits for some years before their technology is profitable.

TABLE 3.7: Survival, growth and profitability of firms with innovation loans compared to firms with venture capital financing: Overall performance

	(1) Active Coef./SE	(2) Deficit Coef./SE	(3) ln(sales+2) Coef./SE	(4) log(va+2) Coef./SE	(5) ln(employees+1) Coef./SE	(6) ln(assets+2) Coef./SE	(7) OROA Coef./SE
Treated		.057	.096*	-.016	-.013	.011	-.045
		(.08)	(.05)	(.11)	(.06)	(.04)	(.05)
After		.274***	.331***	.208	.407***	.540***	-.143***
		(.09)	(.11)	(.13)	(.11)	(.13)	(.04)
Treated*After	-.081**	-.321***	-.120	.105	-.228*	-.233	.220***
	(.03)	(.10)	(.13)	(.15)	(.13)	(.14)	(.05)
Estimation method	Probit	Probit	OLS	OLS	OLS	OLS	OLS
F-value			226.6	43.23	146.7	160.7	6.423
Adjusted R-squared			.8089	.5488	.7609	.7618	.1493
Log-likelihood	-244	-541	-745	-984	-835	-772	-200
Chi-Square	14	78					
No. of obs.	729	931	931	861	933	931	907

Clustered standard errors (SE) at the firm level are reported in parentheses: * significance at ten, ** five, *** one percent.
Note: See Table 3.2 for a detailed description of the table content and the analysis.

Table B.6 in Appendix B.2 displays regressions on the same sample of firms as the regressions in Table 3.7, but with a different model specification splitting the overall *After* and *Treated*After* variables into more detailed pre- and post-treatment time periods. Interestingly, the share of inactive firms is 25.2% higher 5–8 years after treatment for the firms with innovation loans compared to the venture portfolio companies. The remaining estimates for performance 5–8 years after treatment should thus be interpreted in the light of a survival bias. To illustrate the potential impact of the survival bias I assume that the inactive firms have a sales growth of -100%. Based on this assumption the estimated average difference in sales growth 5–8 years after treatment would be -30% (0.252*(-100)+(1-0.252)*-0.77). This suggests a poorer sales growth among the firms with innovation loans compared to the venture portfolio companies. Given the same standard errors, this estimate would be statistically significant at the 10% level. A similar analysis for the post-treatment differences in employee growth, correcting for sample survival bias, also suggests that there is statistically significant lower growth in employees for firms with innovation loans 5–8 years after treatment. A plausible interpretation of the development in the dependent variables is that the firms with venture financing put their resources into expanding with respect to more employees and assets, while the firms with innovation loans focus more on handling their debts by putting more emphasis on running their business with an operating surplus.

Analogous to the comparison of firms with innovation loans with firms with private bank financing, I do not expect the control group of venture portfolio companies to have the same performance distribution as the firms with innovation loans. I expect the firms with venture investments to have a higher growth in the right tail of the distribution. This is based on the assumption that venture backed firms go through a tighter selection process with respect to growth potential compared to the firms with innovation loans.

Table 3.8 compares the performance distribution of the firms with innovation loans and the venture portfolio companies at the 75th percentile, the 90th percentile, and the 95th percentile respectively. To keep it brief only the differences-in-differences estimates are displayed. Note that the control group only contains 34 firms. Thus, estimates at the 95th percentile contain at most two firms with venture financing. It it is important to look at the different quantile regressions in context. If the results at the different percentiles all seem to go in the same direction, then this strengthens the result. Overall the quantile regressions suggest that there are no differences in sales or value added growth 1–8 years after treatment. The venture portfolio companies do, however, have a stronger growth in employment and assets. This may possibly indicate that some of the venture portfolio companies are more likely to succeed in the long run.

Table 3.8: Firms with innovation loans compared to firms with venture capital financing: Quantile regressions.

	(1) ln(sales+2) Coef./SE	(2) ln(va+2) Coef./SE	(3) ln(emp.+1) Coef./SE	(4) ln(assets+2) Coef./SE	(5) OROA Coef./SE
75 percentile					
Treated*2 years before treatment	.035	-.042	-.059	.003	-.022
	(.05)	(.08)	(.05)	(.04)	(.06)
Treated*1 year before treatment	-.000	-.021	-.029	-.000	-.014
	(.01)	(.06)	(.03)	(.01)	(.05)
Treated*(1-2) years after treatment	-.029	-.082	-.241**	-.116	.058*
	(.17)	(.09)	(.10)	(.10)	(.03)
Treated*(3-4) years after treatment	-.066	-.200**	-.178	-.511***	.069**
	(.12)	(.09)	(.24)	(.14)	(.03)
Treated*(5-8) years after treatment	.042	-.285	-.227	-.329***	.061**
	(.12)	(.18)	(.22)	(.12)	(.03)
R-squared	.658	.526	.546	.531	.122
No. of obs.	1053	1053	1053	1053	1053
90 percentile					
Treated*2 years before treatment	-.209*	-.159	-.125	.018	.030
	(.11)	(.19)	(.20)	(.04)	(.06)
Treated*1 year before treatment	.007	-.053	-.061	-.000	.024
	(.02)	(.04)	(.05)	(.01)	(.08)
Treated*(1-2) years after treatment	.038	.039	-.282**	-.074	.090**
	(.11)	(.12)	(.13)	(.16)	(.05)
Treated*(3-4) years after treatment	.071	-.060	-.441**	-.268	.009
	(.11)	(.29)	(.17)	(.20)	(.09)
Treated*(5-8) years after treatment	-.020	-.046	-.378	-.638***	.127**
	(.39)	(.31)	(.27)	(.23)	(.05)
R-squared	.614	.491	.504	.479	.058
No. of obs.	1053	1053	1053	1053	1053
95 percentile					
Treated*2 years before treatment	-.199*	-.120	-.074	.039	-.044
	(.12)	(.08)	(.06)	(.05)	(.08)
Treated*1 year before treatment	-.005	-.133*	-.037	-.015	.075
	(.02)	(.08)	(.05)	(.02)	(.05)
Treated*(1-2) years after treatment	-.039	.100	-.324***	-.321	.160*
	(.18)	(.26)	(.12)	(.30)	(.10)
Treated*(3-4) years after treatment	-.116	-.238	-.513**	-.163	.044
	(.40)	(.27)	(.22)	(.18)	(.08)
Treated*(5-8) years after treatment	-.649	-.699	-.477*	-.995**	.155*
	(.65)	(.61)	(.27)	(.43)	(.09)
R-squared	.579	.456	.471	.441	.014
No. of obs.	1053	1053	1053	1053	1053

Standard errors (SE) are reported in parentheses: * significance at ten, ** five, *** one percent.
Note: The data set and the control variables are the same as in Table 3.7. The only difference is that I replace missing values with zero in order to avoid bias, e.g. due to firms falling out of the sample. See also Table B.4 for interpretation of the estimated coefficients and Table 3.5 for more details on the quantile regression estimation.

3.5 Welfare implications of the innovation loan program

From the comparison with the program rejects, see Table 3.2, the average treatment effect on sales growth from an innovation loan was 0.29 log-points, which is approximately 29%. Among the firms receiving innovation loans the median sales at t-1 before receiving an innovation loan is 5.3 million NOK, see Table 3.1. Thus, for the median firm the average sales increase with 1.6 million NOK per year. In comparison we know that the innovation loan program operates with an expected loss of one third of the portfolio. Thus, given a median loan of 2 million NOK, see Table 3.1, the expected total loss for Innovation Norway on the median firm is 0.7 million NOK. Unfortunately we cannot draw welfare implications from this as we 1) do not know what the counterfactual development really is, due to a likely administrative bias, or 2) what the alternative use of these resources would give us.

Based on the result from the firm level effect study in Section 3.4.2 it is, however, interesting to explore how large the positive spillover effects from the innovative projects should be in order for the innovation loan program to have the same welfare effect as regular business loans. The results from the analysis in Section 3.4.2 suggest that the innovation loan firms are on the same level with respect to growth as firms with private bank loans, but they are more likely to go out of business. Still, even if there is a positive effect on the firms' performance from the program, the program might involve losses and/or transaction costs leading to a net welfare loss for the economy as a whole (Honohan, 2010). In fact, debt losses and administration costs are considerably higher for the innovation loan program compared to that of private banks. The annual administration costs of the program are above 2% of total assets. This is more at the level of a venture capital fund rather than a bank. Moreover, according to the Norwegian central bank the average annual losses relative to the total portfolio of Norwegian business loans were 0.5% during the period 2002–2010. In comparison, the annual average loss rate for the innovation loan program is above 3%.

Private banks should cover administration costs, credit losses[5], and return on their owners' equity from the income of their services. The innovation loan program, however, need only cover administration costs. Thus, the net difference in costs between the innovation loan program and the private bank is the size of the losses on the innovation loan portfolio plus the missing return on this equity.

[5] During the 2008–09 financial crisis many private banks needed public assistance in order to avoid insolvency. Although the Norwegian government provided important measures to improve liquidity, no Norwegian bank needed any direct public funding.

During the period 2004–2009, 1 733 million NOK (EUR 217 mill.) were paid out in innovation loans. Given an expected average loss probability of one third, the government needs to set aside 578 million NOK (EUR 72 mill.) into a loss fund in order to cover future expected losses on the loans granted during the period. Since the losses are covered by the government through taxes, one must also add the social costs of public funds. For example, the Norwegian ministry of Finance operates with a social cost of public funds of 20% in their calculations. Given this rate the total extra costs of the innovation loan program compared to regular business loans are 692 million NOK (EUR 87 mill.) on a total portfolio of 1 733 million NOK.[6]

The loss fund is the government's equity. Unlike regular banks, the innovation loan program does not deliver return on this equity.[7] Thus, the government does not only lose the equity, but also the potential return on this equity compared to e.g. investing this equity into regular banking equity. The average risk free rate, measured by the 10-year Norwegian government bond rate during the period 2004–2009, is approximately 4%. Based on US data the average beta-value for banks during the same period was 1.18.[8] Assuming a market risk premium of 5%, from the capital asset pricing model, this gives a required return on equity of approximately 10%.

In order for the innovation loan program to be as welfare enhancing as regular business credit financing, the spillover effects from the innovative projects must be large enough to outweigh the 692 million NOK in expected losses covered by the government, plus the required return on equity on the loss fund.

Positive externalities arising from investment in R&D and innovation are an important part of the rationale for governments to have an innovation policy. The main challenge with this argument is that it is hard to measure the size and effect of these spillovers with any precision (see e.g. Honohan (2010) or Wieser (2005)).

The main source of knowledge spillovers from innovative projects is likely to come from labor mobility. Based on a sample of Norwegian subsidized IT-failures during the 1980s, Møen (2007) investigates whether there are spillover effects as scientists and engineers from the failed subsidized firms start working at other businesses or start new ventures themselves. Møen (2007) finds that firms which engage former employees from the subsidized firms do not perform any better than the average. Moreover, he finds that the spin-offs from the subsidized firms seem to perform below average. This study, based on Norwegian data, suggests that knowledge spillover effects are highly limited. If the

[6]For simplicity I disregard that the transfers into the loss fund are made at different periods in time. Thus, the amount is not an accurate present value.

[7]The program has delivered small surpluses during the period but well below any normal rate of return on equity.

[8]See link `http://people.stern.nyu.edu/adamodar/`

results are generalizable for other innovation policy programs in Norway, the projects supported by the innovation loan program are not likely to have spillover effects which give rise to a welfare gain large enough to compensate for the 692 million NOK plus returns.

That said, spillover effects are likely to vary between regions, programs and over time depending on factors such as culture, technology shifts, population densities, labor mobility and industry composition. Stucchi et al. (2014) are the first to conduct an evaluation of an innovation policy program which also measures knowledge spillover effects. As part of the evaluation of the Argentinean public innovation program FONTAR, Stucchi et al. (2014) use a similar methodology as Møen (2007), measuring knowledge spillover effects through labor mobility using a panel of employer-employee data. In this case the study's results suggest that the indirect effects on employment, real wages and probability of exports for the firms that employ highly skilled labor from the program participants are almost at size with the direct effects on the firms participating in the program. They find the average direct effect on real wages for the participants of the program to be 6.1%, while the indirect effect on real wages from hiring staff from participating firms is 3.6%. Based on the sample sizes in their matching analysis it seems as if there are about 20% more firms that experience knowledge spillover effects compared to firms participating in the program. Assuming that the firms experiencing direct and indirect effect on average are of equal size, the aggregate indirect effect on real wages is 70% of the total effect.[9] Hence, this study suggests that the indirect effect on labor productivity is quite large.

3.6 Conclusion and discussion of results

The research question I seek to answer is the following: How do the innovation loan program participants perform relative to relevant control groups? In line with most program impact studies I try to measure counterfactual outcome of not receiving support from the program, comparing program participants with program rejects. However, I also go one step further by comparing program participants with control groups that receive similar treatment. Doing this I am able to provide a benchmark in nominal amounts on how large potential positive externalities should be in order for the program to provide welfare benefits on the same level as a particular alternative use of resources.

[9] This is calculated by multiplying the indirect effect on real wages with a factor of 1.2, according to the number of firms affected and dividing it by the direct effect on real wages ($3.5 * 1.2/6.1 = 0.7$)

Comparing with program rejects I find that program participants perform better on a variety of growth measures. Although the sample is likely to be affected by an administrative bias, this result suggests that receiving an innovation loan has a positive effect on firm growth. When comparing with firms receiving private bank financing, I find some weak evidence that the firms with innovation loans on average have higher sales growth after 5–8 years. However, despite a higher risk of becoming inactive, I do not find results suggesting that the firms with innovation loans perform better in the upper quantiles of the distribution compared to firms with private long term credit. The latter result suggests that the innovation loan program does not succeed in financing the target group of innovative projects with a high growth potential.

I compare both firm performance as well as the cost structure of the innovation loan program with that of regular bank activity. Debt losses and administration costs are considerably higher for the innovation loan program compared to that of private banks. One third of the innovation loans are expected to end up as losses, and the administration costs are on the same level as that of venture funds. I find that the knowledge spillover effects from the projects with innovation loans must amount to one third of the amount of credit provided by the program plus the social cost of public funds in order for the program to provide the same level of welfare as regular credit activity towards the business segment. A previous study from Norway on subsidized IT-failures suggests that these spillover effects have limited effect on business performance, while other studies suggest that the spillover effects are large.

I do not find differences in sales growth between firms with innovation loans and firms with venture fund financing. This could indicate that the time period I look at, 3–8 years after the loan was paid out, is a too short time interval to detect commercialisation of innovative projects. An alternative explanation for this result is that neither the innovation loan firms, nor the venture portfolio companies, will end up as commercial successes. Still, the result that venture portfolio companies are less likely to be become inactive, and that they on average put more human and capital resources into their projects compared to firms with innovation loans, may indicate that the innovation loan firms are less likely to succeed in the long run compared to the venture portfolio firms.

The fact that the selected firms perform better than the rejects as well as the fact that I do not find significant differences between the innovation loan firms and the venture portfolio companies suggests that Innovation Norway's selection competency is adequate, at least compared to other private alternatives. In fact, when comparing the performance of firms with market based loans from Innovation Norway with that of private market based loans I do not find statistically significant differences. This suggests that Innovation Norway's bank competency is at level with that of private institutions, although that may not be sufficient to make the program contribute to a net improvement in welfare.

During the period for which I measure firm performance, from 2005–2012, the total number of bankruptcies in Norway was more than 25% higher during the final part of the period compared to the first half. Hence, I cannot rule out that the period which I investigate was a period with particularly adverse macro economic conditions making it difficult for innovative projects to succeed. Still, statistics on returns from European venture funds show that the average performance for each cohort of funds established since the late 1990s has been poor. Moreover, it does not seem that the venture funds established during the 2000s perform worse than those vintages established in the time span five years before or five years after (EVCA, 2014). This illustrates how difficult it is to select future technological champions. Hence, the reason why the innovation loan program does not seem to finance a sufficient amount of innovative success projects is perhaps that this is really a mission impossible as these projects are rare and hard to identify in advance.

References

Angrist, J. D. and J.-S. Pischke (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Athey, S. and G. W. Imbens (2006). Identification and inference in nonlinear difference-in-differences models. *Econometrica 74*(2), 431–497.

Beck, T., A. Demirgüç-Kunt, and V. Maksimovic (2008). Financing patterns around the world: Are small firms different? *Journal of Financial Economics 89*(3), 467–487.

Becker, S. O. and H. K. Hvide (2013). Do entrepreneurs matter? *Available at SSRN 2199645*.

Bennedsen, M., K. M. Nielsen, F. Perez-Gonzalez, and D. Wolfenzon (2007). Inside the family firm: The role of families in succession decisions and performance. *Quarterly Journal of Economics*, 647–691.

Besanko, D. and A. V. Thakor (1987). Competitive equilibrium in the credit market under asymmetric information. *Journal of Economic Theory 42*(1), 167–182.

Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. *American Economic Review 75*(4), 850–855.

Chernozhukov, V. and I. Fernández-Val (2011). Inference for extremal conditional quantile models, with an application to market and birthweight risks. *The Review of Economic Studies 78*(2), 559–589.

Curran, J. (2000). What is small business policy in the UK for? Evaluation and assessing small business policies. *International Small Business Journal 18*(3), 36–50.

EVCA (2014). 2013 pan-european private equity performance benchmarks study.

Foreman-Peck, J. (2013). Effectiveness and efficiency of SME innovation policy. *Small Business Economics 41*(1), 55–70.

Grünfeld, L., G. Grimsby, Høseth-Gilje, H. Hvide, K. O. Lian, H. Steinsvik, and E. Vinogradov (2013). En statlig bro i kapitalmarkedet: Evaluering av Innovasjon Norges låne- og garantiordninger. *Menon publication* (42/2013).

Hall, B. H. (2005). The financing of innovation. *The Handbook of Technology and Innovation Management*, 409–430.

Hao, L. and D. Q. Naiman (2007). *Quantile regression.* Number 149. Sage.

Honohan, P. (2010). Partial credit guarantees: Principles and practice. *Journal of financial stability 6*(1), 1–9.

Khandker, S. R., G. B. Koolwal, and H. A. Samad (2010). *Handbook on impact evaluation: quantitative methods and practices.* World Bank Publications.

Lundström, A., P. Vikström, M. Fink, H. Crijns, P. Głodek, D. Storey, and A. Kroksgård (2013). Measuring the costs and coverage of SME and entrepreneurship policy: A pioneering study. *Entrepreneurship Theory and Practice*.

Machado, J. and J. Santos Silva (2013). Quantile regression and heteroskedasticity.

McKenzie, D. (2010). Impact assessments in finance and private sector development: What have we learned and what should we learn? *The World Bank Research Observer 25*(2), 209–233.

Møen, J. (2007). R&d spillovers from subsidized firms that fail: Tracing knowledge by following employees across firms. *Research policy 36*(9), 1443–1464.

Norrman, C. and L. Bager-Sjögren (2010). Entrepreneurship policy to support new innovative ventures: Is it effective? *International Small Business Journal 28*(6), 602–619.

OECD (2009). The impact of the global crisis on SME and entrepreneurship financing and policy responses.

Oh, I., J.-D. Lee, A. Heshmati, and G.-G. Choi (2009). Evaluation of credit guarantee policy using propensity score matching. *Small Business Economics 33*(3), 335–351.

Ono, A., I. Uesugi, and Y. Yasuda (2013). Are lending relationships beneficial or harmful for public credit guarantees? Evidence from Japan's emergency credit guarantee program. *Journal of Financial Stability 9*(2), 151–167.

Pöyry, Damvad, and Agenda Kaupang (2010). Evaluering av Innovasjon Norge, utarbeidet for Nærings- og handelsdepartementet. *Econ-rapport* (R-2010-054).

Rigby, J. and R. Ramlogan (2013). The impact and effectiveness of entrepreneurship policy. Technical report, Nesta Working Paper.

Samujh, H., L. Twiname, and J. Reutemann (2012). Credit guarantee schemes supporting small enterprise development: A review. *Asian Journal of Business and Accounting 5*(2), 21–40.

Schneider, C. and R. Veugelers (2010). On young highly innovative companies: Why they matter and how (not) to policy support them. *Industrial and Corporate change 19*(4), 969–1007.

Stiglitz, J. E. and A. Weiss (1981). Credit rationing in markets with imperfect information. *The American economic review 71*(3), 393–410.

Storey, D. (1998). Six steps to heaven: Evaluating the impact of public policies to support small businesses in developed countries. *Warwick Business School, WP 59.*

Stucchi, R., S. Rojo, A. Maffioli, and V. Castillo (2014). Knowledge spillovers of innovation policy through labor mobility: An impact evaluation of the FONTAR program in Argentina.

Takalo, T. (2009). Rationales and instruments for public innovation policies. Technical report, ETLA discussion paper.

Uesugi, I., K. Sakai, and G. M. Yamashiro (2010). The effectiveness of public credit guarantees in the Japanese loan market. *Journal of the Japanese and International Economies 24*(4), 457–480.

Valentin, A. and B. Wolf (2013). Credit guarantee schemes and their impact on SME lending: Existing literature and research gaps. *International Journal of Entrepreneurial Venturing 5*(4), 391–405.

Wallsten, S. J. (2000). The effects of government-industry R&D programs on private R&D: The case of the small business innovation research program. *RAND Journal of Economics 31*(1), 82–100.

Warwick, K. and A. Nolan (2014). Evaluation of industrial policy.

Wieser, R. (2005). Research and development productivity and spillovers: Empirical evidence at the firm level. *Journal of Economic Surveys 19*(4), 587–621.

Chapter 4

Aging business owners' and CEOs' impact on firm performance

Abstract: Along with the demographic changes in the general population there has been a sharp increase in the share of business owners above 55 years of age. The EU has focused on transfer of business ownership as the critical point associated with owners approaching retirement age. This paper investigates what happens to firm performance prior to the retirement of the firms incumbent owner and CEO. The results suggest that firms with older owners and CEOs experience reduced firm level investments and employment. Particularly, I find evidence suggesting that productivity falls in firms with older CEOs. The aggregate productivity loss in Norway due to older CEOs is estimated to be 0.2% of Norwegian mainland GDP. The size of the potential average welfare gain from replacing an older CEO with a younger and more productive colleague is increasing in the firm's size and decreasing in the CEO's likelihood of choosing retirement as his preferred outside option.

4.1 Introduction

Building on Schumpeter's 1934 seminal work, there now exists an extensive empirical and theoretical literature focusing on how businesses are created. Particularly, it is now well documented that people are less likely to start a new venture and become entrepreneurs after they pass a certain age (Parker, 2009; Kautonen et al., 2014). Business start-up, although essential, is only a part of the life cycle of the entrepreneur. Few studies focus on what happens with the venture as the entrepreneur matures. This paper focus on how the aging of existing entrepreneurs affects their business' performance.

A key novelty in this paper is to try to separate the age effect from the role as owner and CEO. Many empirical studies put an equality sign between business owners and entrepreneurs (Parker, 2009). As emphasized by Berglann et al. (2011), however, the most interesting aspect of the entrepreneur is the dual role of employing both human and financial capital into a business. Thus, the term entrepreneur is not suited to distinguish between the owner and the manager role in the firm. In this paper I therefore use the terminology *firm owner* and *firm CEO*, rather than their combined designation embodied in the term *entrepreneur*.

As a part of the "EU 2020" jobs and growth strategy, the EU is focusing on measures which can facilitate business transfer for small and medium sized enterprises (SMEs). The backdrop for this is Europe's aging population. Policy makers are concerned that jobs will be lost if businesses close down when their founding owners retire (European Commission, 2006). Dating back to 2002, the "BEST-project expert group" estimated that within the next 10 years approximately one third of European enterprises would need successors (European Commission, 2002). During the 10–year period that passed there were quite a few transfers of business ownerships. Among Norwegian firms, one out of five firms changed majority owner over the 10–year period 2000 to 2009. Still, although there have been many transfers of firm ownership, the fraction of Norwegian majority stake firm owners older than 55 years increased from 24% in 2000 to 33% in 2009. Other countries facing similar demographic changes as Norway are also likely to experience an aging population of business owners.

The EU has focused on how they can better facilitate for business transfer processes in order to avoid losing productive firms and jobs as their owners retire (European Commission, 2011). Just as important, and what I study in this paper, is what happens with the firms in the period before their owners and managers choose to retire. If it turns out that business owners start preparing for retirement by gradually reducing the activity level of the firm, many of the jobs may already be gone before the potential transfer of ownership.

The paper presents evidence suggesting that the aging of owners, as well as CEOs, leads to a gradual reduction in firm level investments and employment. The results are derived using a fixed effect model on a full population data set of Norwegian limited liability companies during the 10–year period 2000 to 2009. I identify a negative effect on the amount of firm investment for owners older than 60 years of age. The point estimate is, however only statistically significant for owners between 71 and 75 years of age. For employment I find a negative effect of owner age on employment for owners older than 65 years of age, although only statistically significant for firm owners between 66 and 70 years of age. With respect to aging CEOs I find a persistent statistically significant negative effect on firm employment starting at CEO ages between 51 and 55. Moreover, I identify a persistent negative effect on investments from CEO age starting five years later, suggesting that the firm level decline in employment leads the decline in investment activity. The results are robust controlling for firm level fixed effects, ownership transfers, change of CEO as well as firm age and business cycles.

I do not find any statistically significant effects from owner age on firm value added or productivity. This, may suggest that the owner's skills do not deteriorate with age. When it comes to CEOs, I find statistically significant effects from CEO age on firm value added. Much of the reduction in value added is due to a downscaling effect, following a reduction in labor and capital inputs into production. However, I find evidence that part of the reduction in value added is due to a negative effect on firm level productivity. A downscaling of the firm's production due to fewer employees and less capital need not involve an efficiency loss. On the contrary, this can be a healthy market mechanism leading to a reallocation of resources from downscaling firms to growing firms with higher productivity. The latter depends on whether the economy's labor market is well functioning with respect to facilitating a smooth transfer of labor resources into alternative productive use. A reduction in firm level productivity, however, involves by definition a less efficient use of resources.

Given rational and profit maximizing firms one should not on average expect to observe any negative effect from aging of firm owners or CEOs. The owner, however, is the only person in the firm without a principal. In order to adjust for any potentially negative age effect the owner must decide to let a new owner replace himself by transferring the control of the business. Thus, an important question is whether there are arguments for policy makers to provide stronger incentives for conducting ownership transfers at an earlier age. Although I do not find evidence of any negative productivity effects of aging owners, in two out of three firms the owner and the CEO are the same person. Thus, transfer of ownership and changing the CEO may often be concurring events.

Taken at face value, the decline in value added of the firms due to reduced productivity associated with aging CEOs represents 0.2% of Norwegian mainland GDP. Whether it is desirable, or even possible, from the social planner's point of view to replace incumbent CEOs at an earlier age depends on the availability of alternative younger managers with suitable profiles, the size of the firm, as well as whether the incumbent CEO can find alternative productive occupations either within or outside the firm.

This paper proceeds as follows. In Section 4.2 I describe the role of the firm owner and present potential mechanisms affecting firm performance through the aging of its firm owner. In Section 4.3 I introduce the data set applied for the analysis, the dependent variables, as well as sample summary statistics. The data set is unique in the sense that I have combined firm level ownership data over a period of 10 years. In Section 4.4, I first present the econometric model and choice of estimator before presenting the regression results. In Section 4.5 I provide robustness tests on the regression results, and in Section 4.6 I estimate and discuss the aggregate productivity effects at the national level as well as potential policy implications of aging owners and CEOs. Finally, Section 4.7 summarizes the paper.

4.2 Business owners and the effect of aging

As a background for why aging of the business owner can lead to a change in firm performance, this section presents a framework for understanding the function of the business owner as well as hypotheses on how these functions may be affected by age.

4.2.1 The four owner roles

One instructive way to think about the different roles of the business owner is proposed by Grünfeld and Jakobsen (2006). They emphasize four roles of the business owner. Good business owners are characterized by combining these roles in such a way that they increase the value of the firm compared to alternative owners.

First of all, a good owner should possess *selection competency*. Selection competency is the ability to detect and invest in firms or ideas with a high potential, and where the potential increases from having this particular owner, as opposed to other potential owners. Selection competency is key for any successful entrepreneur, either starting a business from scratch or taking over a business from the entrepreneur who started the venture. Second, a good owner should possess *complementary resources* to the firm. Complementary resources are resources that the firm does not possess without that particular owner. This could for example be industry experience, organizational skills, or a business network for bringing in new competency, customer or supplier relations to the firm. This role of the owner coincides much with what is traditionally thought of as the role of the manager. This type of active ownership is considered an essential part of what venture funds add to the development of their portfolio companies. Third, the owner must have *fueling competence*. This means that the owner must be able to provide a sufficient amount of capital at the right moment in time. Finally, the business owner must be able to *govern* the company in a good manner. This includes making the right strategic choices in interaction with the management, or at least selecting the right manager to do so, and controlling that the firm's strategy is implemented in a good manner.

4.2.2 Owner age and firm performance

All people that become old of age will at some point in time experience reduced capacity. The process of aging does, however, also have more indirect effects which can lead to changes in the execution of the owner roles, which in turn affect firm performance. This could be changes over time in the business owner's personal characteristics such as ambitions, business network, experience, discount rates, risk preferences and access to financial capital. Most of the potential explanations presented here are, unfortunately, not testable in my data set. Still, I believe the discussion is useful as it creates a common understanding of what type of effects one might expect with aging business owners.

Ebner et al. (2006) find evidence that people tend to choose age-appropriate goals. Particularly, they find that people with age shift from growth orientated goals towards more focus on maintenance and loss prevention. They suggest the reason for this change in motivation is that people unconsciously adapt to changing developmental opportunities and constraints coming with age by changing to the goal which at any time maximizes gains and minimizes losses. Following this line of thought we would expect a shift in goal orientation if the business owner experiences changes in his capabilities with advancing age. Thus, changes in the business owner's motivation on behalf of his firm are likely to be dependent on changes in other underlying characteristics such as physical and mental health, experience, and business network. If the motivation changes and the business owners hold on to their position, this may have a negative impact on firm performance.

In the entrepreneurship literature, age is recognized as an important determinant of the propensity to become an entrepreneur (Parker, 2009). Kautonen et al. (2014) find that the probability of starting a business for those entrepreneurs who aspire to hire workers is increasing up to the late forties and decreasing thereafter. One possible mechanism at work, suggested by Levesque and Minniti (2006), is that the opportunity cost of time increases as people's remaining life expectancy shortens. This in turn makes older people operate with a higher discount rate on future earnings. Levesque and Minniti (2006) point out that the hypothesis of increasing discount rates with advanced age applies to any income producing activity involving sunk costs and an expected stream of payments into the future. Thus, following the same reasoning, one would expect business owners to be less willing to invest time and financial resources into their business as they become older. Linking this to the four roles of the business owner, one can say that age has an effect both on the owner's *selection and fueling competency* as age reduces the incentive for detecting and investing in ideas with great potential.

There are also studies suggesting that there is a tendency of increasing aversion towards risk with age (Bakshi and Chen, 1994; Morin and Suarex, 1983; Pålsson, 1996). Increased risk aversion with age has the same effect on business owners' behaviour as increased discount rates. One potential explanation for increased risk aversion is that as the business owners approach retirement age they have less time remaining to make up for any loss in the case of a bad realization of an investment in the firm. If increased risk aversion is the case, then, consistent with Ebner et al. (2006), this would probably induce a gradual shift in motivation of the business owner towards maintenance and loss prevention, rather than growth.

The owner's *fueling competency* is not only dependent on the ability to assess the timing of investments, or divestments, but also on the owner's access to finance. In Levesque and Minniti's (2006) model people's access to finance is assumed to be positively influenced by age. The argument is that older people are more likely to have accumulated wealth. However, although older people are likely to be wealthier and have more assets available as collateral, older people may pose a greater operational risk for creditors. This could follow from the combination of an expected shorter time remaining as business owners, the expected stream of future payments associated with this ownership, and the uncertainty related to the market value of SMEs. In fact, Engel et al. (2007) find that owners older than 50 years of age seem to have special difficulties with obtaining loans. Thus, controlling for personal wealth, is seems as if older age weakens the owner's access to financing. Neuberger and Räthke-Döppner (2014), do not, however, find that owner age has a negative impact on loan rates among those that do receive credit financing.

Several studies provide evidence suggesting that there is a decline in the average level of cognitive abilities with age, see e.g. Miller et al. (2009); Verhaeghen and Cerella (2002); Verhaegen and Salthouse (1997)).[1] It is the fluid intelligence, the ability to solve novel problems, as well as the processing speed that seem to be negatively affected by age (Stuart-Hamilton, 2012; Miller et al., 2009). This type of decline in cognitive abilities can lead to bad strategic choices of the owner which in turn affect firm productivity. In fact, Waelchli and Zeller (2013) suggest that deteriorating cognitive abilities are the main driver of the negative age effect they observe from the chairman of the board on return on equity. One should, however, keep in mind that the owner's ability to fulfill the four roles to a large extent is dependent on experience and verbal skills. This is a type of intelligence not influenced by age. Thus, I would not expect to find a significant effect on firm productivity due to the owner's weakened cognitive abilities with age.

[1] In fact, age related declines are incorporated into the calculation of IQ in order to distinguish between normal age-related decline and impairment due to neurological or psychiatric disorders (Miller et al., 2009). There is, however, uncertainty attached to both the size of the age-related decline in cognitive abilities as well as when this decline begins. Cross-sectional studies are accused of exaggerating the effect as they also capture non-age related differences between cohorts. Longitudinal studies, which tend to find a smaller effect, are influenced by test learning effects and drop out bias, see e.g. Stuart-Hamilton (2012) and Salthouse (2014).

While many owners are likely to retire when their ability or motivation is reduced with age, others may carry on even though it may have a negative impact on business performance. Whether it from a social perspective is desirable and/or possible to change the owner will depend on what the reason for not retiring is. Potential explanations for why owners chose not to retire are that 1) they do not recognize their reduced abilities as owners, 2) they enjoy their position, and value it higher than having the business run optimally, or 3) there exist no better alternative owners. If there are no better alternatives to the incumbent owner, then the best alternative is not to retire. However, if the reason for not retiring is that the owner fails to recognize deteriorating abilities, or that there are non-monetary personal gains from staying in position, then there may exist welfare-improving policies.

4.3 Data, dependent variables, and descriptive statistics

The data used for the analysis are based on register data for all firms registered in the Norwegian Register of Business Enterprises. The register includes all Norwegian limited liability firms as well as all other forms of business organizations with a certain minimum level of economic activity. The database covers approximately 95% of Norwegian business activities. It includes annual accounts data, balance sheet figures, ownership structures, board composition, in addition to firm specific information such as industry affiliation, number of employees, date of firm establishment and geographical location.

I focus on firm owners with full control over their firm during the 10–year period 2000 to 2009. The control criterion is exercised in the strongest sense, requiring all owners to hold a ownership stake of 50% or more. I have traced back ownership structures through subsidiaries and holding structures to identify the ultimate personal firm owner. To be classified as an ultimate majority owner it is sufficient to have majority ownership at each level of the ownership chain.

Firms with two owners holding a 50% stake each are excluded from the data set. Similarly, in order to avoid ambiguous age effects, I exclude firms with more than one CEO from the sample. The majority of firms in the register are very small, often not employing more than the owner himself. To exclude self-employing and part time entrepreneurs I discharge all firms with less than two employees and which do not have 1 million NOK (EUR 130 000) or more in labor costs during any of the years in the 10–year period 2000 to 2009. Thus, the sample of business owners which I analyze contains the owner-manager type of entrepreneur who seeks to own and run a business and invest in it, as well as business owners who are not employed in their business. Furthermore, I exclude financial and real estate firms from the sample because the nature of their investments is different from other types of firms.

Finally, I exclude firms with less than three years of consecutive observations, firms with missing investment observations as well as firms with illogical values such as negative capital stock or investment-capital ratios smaller than -1. The final sample contains all together 24,157 firms and a total of 166,137 firm-year observations.

4.3.1 Dependent variables

Investigating the impact of aging owners on firm performance I focus on three measures: Real investments, employment, and value added. These measures capture different aspects of the owner's ability and willingness to develop the firm over time.

Ultimately it is the owner who controls capital flows in and out of the firm. Thus, real investments is a natural variable to start with when investigating whether there exists an effect of owner age on firm performance. Although investment is no direct measure of firm performance, it is an important part of firm behaviour, and it is likely to give us information on how the firm may perform over time.

Capital expenditures and labor will in practice often be complementary input factors. Hence, if the investment level changes with firm age, I also expect the employment level to change with it.[2]

A firm's value added is a function of capital expenditures and employment, as well as factor productivity. Thus, if capital expenditures and employment are affected by aging owners, then value added will by definition follow. Controlling for labor and investment goods one can also study how aging firm owners have an effect on total factor productivity.

Profitability is the most important parameter of a firm owner's success. Cucculelli and Micucci (2007), to my knowledge the only existing paper which studies the impact of aging owners on firm performance, find that the aging of the firm's founder has a positive impact on the return on total assets (ROA) until a certain age before its contribution turns negative. The sample of firms I study contains unlisted firms without a market valuation of assets. The problem with unlisted firms is that write-offs are based on accounting rules that tend to make the book value of equity deviate from its true value over time. Profitability measures such as return on equity (ROE) and return on total

[2] Larger technological shifts might lead to a reduction of manpower due to automation of certain task. Hence, capital and labor can also be substitutes. However, in most cases they will be complements at the firm level.

assets (ROA) will therefore be positively biased over time. In fixed effect studies, where the control group is the firm itself over time, return measures which are calculated based on book value of assets will consequently be biased. Hence, even though profitability is a highly relevant measure of firm performance for firm owners, I do not attempt to pursue the impact of owner age on profitability in this paper.

4.3.2 Descriptive statistics

Summary statistics for the full sample of personal majority owned firms is displayed in Table C.1 in appendix. The descriptive statistics shows that the sample distribution of firms contains mostly small firms with a long thin tail of larger firms to the right. Thus, sales, value added and labor costs all have a mean which is higher than the 75 percentile. It is also interesting to note the median real investment is 34,000 NOK (EUR 4,250), while the average real investment is 423,000 NOK (EUR 52,800). Moreover, the average investment ratio is 4.3%, while the median investment-ratio is 1.3%. This is unsurprising as investments are made in lumps and that investments are small in most years, see e.g. Nilsen et al. (2009).

Moreover, the sample descriptive statistics in Table C.1 shows that the average age of firm owners is 49.4 years, just above the median age of 49.0. The distribution of owner age is approximately bell shaped with the 25 percentile and 75 percentile at minus seven and plus eight years from the median value. This means that 50% of the owners are in the relatively narrow age span 42 to 57 years. There are fewer observations on CEO age because the identity of the CEO is missing from my data set for the year 2006. The CEO is on average 1.6 years younger than the owner, while the median CEO is one year younger than the median owner age. This pattern is also robust if we discard the owner age observations in 2006. The mean of the $OwnerCEO$ variable tells us that in 68% of the sample the owner is also the firm's CEO. Thus, two thirds of the sample is what Kautonen et al. (2014) refer to as manager-owner entrepreneurs.[3]

Table C.2 in appendix displays the distribution of owners across age groups. The table uses the same 5-year age cohort dummies as I later apply in the regression analysis. The table shows that the number of owners per age cohort drops sharply after the owners turn 60. While about one third of all owners are in their fifties, less than 15% are in their sixties and seventies. The official retirement age to be entitled to full pension in Norway during the period 2000 to 2009 was 67 years. Thus, similar to regular employees, the table illustrates that firm owners also "retire" at an increasing rate during their sixties.

[3] Kautonen et al. (2014) distinguish between three types of entrepreneurs: *owner-managers*, *self-employers*, and *reluctant entrepreneurs*.

From Table C.3 we also see that firm CEOs follow a similar age distribution as firm owners, although the relative share of older CEOs is generally lower.

Figure C.1 shows how the age distribution of firm owners changed from 2000 to 2009. We see that the share of owners between 55 and 75 years of age has increased from 2000 to 2009. This suggests that a larger share of owners has postponed the decision to transfer their business to new owners.

4.4 Empirical strategy and results

In this section I study how firm owner and CEO age, and the combination of the two, affect firm investments, employment, and value added.

4.4.1 Firm investment

Testing aging owners' and CEOs' impact on firm investments I apply the following model:

$$\begin{aligned} ln(I_{i,t}) = \beta_1 * OwnerAge_{i,t} + \beta_2 * CEOAge_{i,t} + \beta_3 * OwnerCEOAge55_{i,t} + \\ \beta_4 * OwnershipTransfer_{i,t} + \beta_5 * CEOChange_{i,t} + \beta_6 * FirmAge_{i,t} \\ + \beta_7 * Year_{i,t} + u_{i,t}, \quad \text{for} \ \ i = 1, \ldots, N; t = 1, \ldots, T, \end{aligned} \tag{4.1}$$

where i is the firm index, N is the total number of firms, t is the time index, and T is the length of the time series.

The dependent variable $ln(I_{i,t})$ is the natural logarithm of real investments. The real investment variable is derived from the firm's annual accounts by calculating year on year changes in non-financial capital stock plus write-offs and write-downs. These investment figures can be both positive and negative depending on whether capital expenditures are larger or smaller than capital sales. In fact, 15% of our net investment figures are negative. I handle this by left censoring the sample by setting all remaining negative investment figures equal to one before taking the natural logarithm.

$OwnerAge_{i,t}$ is the age of the majority owner of firm i at time t. Owner age is included in the regression model as a set of dummy variables representing owner age at five year intervals above 50 years of age until 75 years. The advantage of the dummy variable model is that it allows for a very flexible functional form with respect to how and when age affects firm performance. All owners older than 75 years of age are placed into the same group. Salthouse (2009) find evidence that age-related decline in non-verbal cognitive abilities seem to start as early as in peoples' 20s and 30s, while the speed of decline is much higher for adults older than 60. I choose owners at 50 years or younger as my benchmark age group. This benchmark corresponds with earlier studies which identify a weakening in cognitive abilities starting somewhere from 50 to 70 years of age (Stuart-Hamilton, 2012, p. 52).

$CEOAge_{i,t}$ is the age of the firm's CEO. CEO age is specified in an identical manner as firm owner age in the model. Lundstrum (2002) find that long term investment in research and development is decreasing with the age of the CEO. He suggests that this results follows from shareholders putting more emphasis on short term projects as the hold-up problem increases with the CEOs age. Serfling (2012) document that older CEOs invest less than younger CEOs, and that this finding is concentrated in firms with larger growth opportunities, suggesting an underinvestment problem. In order to be able to distinguish between the age effect of aging owners and aging CEOs on firm investments it is important that CEO age is also included in the model. The owner and the CEO are, however, often the same person, and the age estimates will thus be based on the remaining sample where the owner and the CEO are not the same person and not of the same age. Although this multicollinearity problem should not provide biased estimates, it does inflate the standard errors of the age coefficients. This may in turn lead to a rejection of the hypothesis that there is an effect from the age of owners and/or CEOs on firm investments.

$OwnerCEOAge55_{i,t}$ is a dummy variable indicating whether the firm owner is older than 55 years and holds position as CEO. By controlling for owner-managers interacted with owner age, I investigate whether the separation of ownership and control has an impact on firm investments as the owner-manager becomes older. A negative effect from the owner-manager dummy would indicate that having ownership and control concentrated with one individual is an impediment towards adjusting the firm's control structures so as to avoid the negative age effect on performance (see Fama and Jensen (1983) and Goyal and Park (2002) for literature on the benefits of separation of firm ownership and control).

$OwnershipTransfer_{i,t}$ and $CEOChange_{i,t}$ are dummy variables taking on the value 1 ex-post a transfer of ownership or a change of CEO, respectively. Marshall et al. (2006) find that firm owner age is positively correlated with having formal succession plans for the business. Thus, to separate the effect of changing owner or CEO from that of changing age, I control for changes of ownership and CEOs in the regression. Moreover, it is important to control for ownership transfers and CEO changes as otherwise one could mistake such changes from an older individual to a younger one for an age effect, while it really is an effect from ownership and CEO changes independent of age.

$FirmAge_{i,t}$ is the number of years since the firm was established. Firm age is included in the model by a set of dummy variables representing firm age at five years intervals from zero years all the way up to 50. Firms older than 50 years are placed into the same group. Several studies have proposed firm age as a possible cause for deteriorating firm performance (see e.g. Loderer and Waelchli (2010); Nunes et al. (2013); Habib et al. (2013); Cooley and Quadrini (2001); Evans (1987)). Since firm age and owner age are highly positively correlated, not controlling for the one or the other may lead to a severe omitted variable bias. Loderer and Waelchli (2010) suggest that the negative relationship between firm age and investments is due to older firms having less profitable investment opportunities. They hypothesize that the decay in profitability among older firms is due to a cementation of organizational rigidities over time and/or increasing rent-seeking behavior inside the firm with time. They do, however, not control for firm owner age, which may be an additional explanatory factor. Habib et al. (2013) develop a theoretical model which explains how a decrease in profitability with higher firm age can be caused by a more dispersed product portfolio with the firm's age.

$Year_{i,t}$ includes time dummies for each year in the panel. These dummies control for time specific effects. The model's error term is captured by $u_{i,t}$.

Firm fixed effect model

The regression analyses are performed within the framework of a fixed effect model. I choose the fixed effect model as the consistency of the random effects model is rejected by the Hausman test. In a fixed effect model, all variables enter as deviations from their average over time. This has the convenient feature that all variables that do not vary over time are implicitly controlled for as they drop out of the model. In fact, there are good reasons to believe that there are unobservable individual specific effects which are correlated with the regressors. For example, it is likely that older owners are over-represented in "sunset industries" which experience declining demand and fewer profitable investment opportunities.

Regression results

Table 4.1 displays the results of three regression analyses. The first regression focuses on the effect of owner age on firm real investment, in the second I add CEO age to the model, while in the third I also test for whether there is an additional age effect when the owner and the CEO are the same person. The dependent variable is on natural logarithmic form, thus, as an approximation the estimated coefficients can be interpreted as percentage points. All owner age estimates are relative to owners at 50 years or younger, while CEO age estimates are relative to CEOs at 50 years or younger. To keep it brief, estimates on the effect of firm age and year dummies are not displayed.

The results in Column 1 suggest that there is a statistically significant negative relationship between firm investment and firm owner age starting at firm owner ages between 56 and 60 years. We also see that the size of the negative effect on investment gradually increases until the age cohort 66 to 70 years of age. For owners of between 56 and 60 years of age firm real investment is on average estimated to be 9.8% lower as compared to firms with owners at 50 years or younger. Moreover, firms with owners in the age group between 61 and 65 invest 20.2% less than owners of 50 years or younger, owners at age 66 and 75 invest 31.6% less, owners at 71 to 75 invest 35.9% less and owners older than 75 years of age invest 29.1% less. The estimated age effect of owners between the ages of 56 and 75 is statistically significant at the 1%. Although the cohort of owners older than 75 years of age comprises less than 1% of all observations, see Table C.2, the estimate is statistically significant at the 5% level.

In Column 2 CEO age is included as a control variable. Starting from the top of Column 2, we see that the owner age estimates are negative for owners older than 60 years of age. The absolute size of the estimated effect of owner age displayed in Column 2 is smaller than in Column 1, although not significantly different at the 5% level. In Column 2 the owner age coefficients are statistically significant only for the owner age cohorts 61–65 and 71–75. The coefficient for owners between 66 and 70 years of age is, however, almost statistically significant at the 10% level (p=0.104). One should keep in mind here that the standard errors of the estimates on firm owner age and firm CEO age are likely to be exposed to problems of multicollinearity as firm owner and CEO are the same person in two out of three firms.

Furthermore, Column 2 shows a negative effect from CEO age on firm investments. The estimated coefficients are negative and statistically significant starting from CEOs at ages between 56 and 60 years of age. Similar to the age effect from firm owners, the estimates suggest that the negative effect on investments increases with CEO age. The effect is statistically significant at the 1% level for CEOs at ages between 56 and 70. The estimate for CEOs between 71 and 75 years of age is almost statistically significant at the 10% level (p=0.105), while for CEOs older than 75 years of age the estimate is statistically significant at the 5% level. Thus, it appears that much of the effect of aging owners observed in Column 1 is in fact due to aging CEOs.

In Column 3 I also control for whether there is an extra age effect when the firm owner is also the firm's CEO and older than 55 years age. From the table we see that there is no additional negative age effect on investments if the firm owner is also the firm's CEO. This suggests that there is no additional negative age effect for firms that do not have any external control mechanisms for CEO performance. In Column 3 we see that there is a statistically significant negative effect on investments at the 5% level for owners at ages between 71 and 75. The coefficients for owners between 61–65 and 66–70 years of age are, however, almost statistically significant at the 10% level (p-value of 0.110 and 0.115, respectively). The CEO age estimates are similar to those described for Column 2.

To sum up, the results in Table 4.1 suggest that there is on average lower investment activity in firms with older owners, and in particular older CEOs. There is, however, no evidence suggesting that firms with owner-managers experience an additional negative age effect on firm investments. In Section 4.5 I perform robustness tests on the results replacing log-investment with a dummy for investment spikes as the dependent variable.

4.4.2 Firm employment

In this section I investigate how firm owner age and CEO age affect firm employment. The regression model is the same as described in Equation 4.1 Section 4.4.1, except that the dependent variable is replaced by log-employees.

Table 4.2 Column 1 shows that the number of employees starts decreasing with firm owners older than 55 years of age. Similar to what we saw for investments in Table 4.1 Column 1, the negative effect on employment starts with owners between 56 and 60 years of age and increases gradually until the age cohort 66 to 70 years of age. For owners between 56 and 60 years of age I find a small negative effect on employment of 1.2% compared to owners at 50 years or younger. Correspondingly, owners at age 61 to 65 employ 4.3% less, while owners between 66 and 70 years of age employ 9.1% less, owners between 71 and 75 employ 8.4% less, and owners older than 75 years of age employ 8.3% less. The estimate for owners at ages between 56 to 60 is statistically significant at the 5% level, while the estimates for owners older than 60 years of age are statistically significant at the 1% level. From Column 1 we also see that there is a statistically significant positive effect on employment of 1.9% from ownership transfers.

From Column 2 we see that the negative effect on firm employment associated with firm owner age is no longer statistically significant. The exception is owners at ages between 66 and 70 years of age. In addition, the coefficient for owners between 71 and 75 years of age is almost statistically significant at the 10% level (p-value=0.104). Interestingly,

Table 4.1:
Estimated effects on firm real investment of owner and CEO age.

	(1) Coef./SE	(2) Coef./SE	(3) Coef./SE
OwnerAge51to55	-.041	-.056	-.056
	(.03)	(.05)	(.05)
OwnerAge56to60	-.098***	.004	.008
	(.03)	(.06)	(.06)
OwnerAge61to65	-.202***	-.111*	-.107
	(.04)	(.07)	(.07)
OwnerAge66to70	-.316***	-.137	-.133
	(.06)	(.08)	(.08)
OwnerAge71to75	-.359***	-.300**	-.297**
	(.10)	(.12)	(.12)
OwnerAge> 75	-.291**	-.071	-.068
	(.14)	(.17)	(.17)
CEOAge51to55		.004	.004
		(.05)	(.05)
CEOAge56to60		-.161***	-.152***
		(.05)	(.06)
CEOAge61to65		-.168***	-.158**
		(.06)	(.07)
CEOAge66to70		-.357***	-.346***
		(.09)	(.09)
CEOAge71to75		-.236	-.225
		(.15)	(.15)
CEOAge> 75		-.441**	-.434**
		(.22)	(.22)
Owner-CEOAge> 55			-.018
			(.04)
OwnershipTransfer	.067	.060	.060
	(.04)	(.05)	(.05)
CEOChange		-.033	-.034
		(.04)	(.04)
FirmAge(d)	YES	YES	YES
Year(d)	YES	YES	YES
F-value	33.06	21.09	20.45
R-squared	.006	.0065	.0065
No. of obs.	166,137	126,130	126,128

Note: This table reports the estimated effect on log-real investments on a panel data set covering the years 2000 to 2009. The regression model is described in Equation 4.1. The independent variables of main interest are firm owner age, CEO age, and owner-manager age. The results are derived applying fixed effect estimation. See Table C.7 for variable definitions. Standard errors are reported in parentheses: * significance at ten, ** five, *** one percent.

we also see that there is a small positive effect on employment for owners between 56 and 60 years of age. This effect is, however, small and only statistically significant at the 10% level.

Column 2 displays a statistically negative effect on employment from CEO age starting already at the ages between 51 and 55. Again, similar to the results on firm investments, we observe that the negative effect on employment seems to increase as the CEO becomes older. All CEO age estimates are statistically significant at the 1% level. The fact that we observe a negative effect on firm employment for CEOs at the ages between 51 and 55, while the effect on investment seems to start at ages between 56 and 60, could suggest that the cut down on employees due to CEO age leads to reduced capital expenditures. I have not pursued this link further. From Column 2 we also see that transfer of ownership as well as change of CEO are associated with increased employment.

In Column 3 I also control for whether there is an additional age effect on employment when the firm owner and the CEO are the same person, and the person is older than 55 years of age. We see from the table that the estimates in Column 3 are very similar to the estimates in Column 2, while there seems to be no additional age effect on employment when the owner and the CEO are the same person.

4.4.3 Firm value added

In the first part of the analysis in this section I investigate the impact on firm value added applying a similar model as described in Equation 4.1 Section 4.4.1. The main difference is that I replace log-investments with log-value added as the dependent variable. 4% of the value added observations in my sample are negative. Thus, similar to what I did to firm investments, I left censor all negative value added observations by setting them equal to one. In order to control for industry specific effects over time I include industry specific time dummies in the model.

Table 4.3 Column 1 shows a statistically significant negative effect on firm value added starting from firm owners between 56 and 60 years of age. We also see a statistically significant effect from transfer of firm ownership. Controlling for CEO age, Column 2, the firm owner age effect on value added is small and insignificant. From Column 2 we see, however, that there is a statistically significant negative effect from CEO age starting from the age cohort 51 to 55. The estimated CEO age coefficients are all statistically significant at the 1% level. We also see a positive effect on value added from changing CEO. In Column 3 I include an additional explanatory variable— controlling for whether there is an additional age effect from firm owner and CEO being the same person. I do

Table 4.2:
Effects on employment of owner and CEO age

	(1) Coef./SE	(2) Coef./SE	(3) Coef./SE
OwnerAge51to55	-.001	.013	.013
	(.00)	(.01)	(.01)
OwnerAge56to60	-.012**	.017*	.019*
	(.01)	(.01)	(.01)
OwnerAge61to65	-.043***	-.010	-.008
	(.01)	(.01)	(.01)
OwnerAge66to70	-.091***	-.049***	-.048***
	(.01)	(.02)	(.02)
OwnerAge71to75	-.084***	-.036	-.034
	(.02)	(.02)	(.02)
OwnerAge> 75	-.083***	-.003	-.003
	(.03)	(.03)	(.03)
CEOAge51to55		-.023***	-.023***
		(.01)	(.01)
CEOAge56to60		-.046***	-.043***
		(.01)	(.01)
CEOAge61to65		-.064***	-.060***
		(.01)	(.01)
CEOAge66to70		-.114***	-.110***
		(.02)	(.02)
CEOAge71to75		-.151***	-.147***
		(.03)	(.03)
CEOAge> 75		-.199***	-.196***
		(.04)	(.04)
Owner-CEOAge> 55			-.006
			(.01)
OwnershipTransfer	.019**	.018**	.018**
	(.01)	(.01)	(.01)
CEOChange		.026***	.025***
		(.01)	(.01)
FirmAge(d)	YES	YES	YES
YearDummies(d)	YES	YES	YES
F-value	79.09	51.98	50.43
R-squared	.0146	.0161	.0161
No. of obs.	163,100	124,511	124,509

Note: This table reports the estimated effect on log-employment on a panel data set covering the years 2000 to 2009. The right hand side variables of the regression model are the same as described in Equation 4.1. The results are derived applying fixed effect estimation. See Table C.7 for variable definitions. Standard errors are reported in parentheses: * significance at ten, ** five, *** one percent.

not find an additional age effect on value added when the firm owner and the CEO is the same person. The estimates in Column 3 are very similar to the estimates in Column 2.

As returns to labor and capital are the main components of value added, the results displayed in Column 1–3 are as expected given that we had already documented a negative relationship between age of the owner and CEO and firm investments and employment. The most surprising is that even though we found some evidence that owners older than 60 years of age are associated with reduced investments and employment, we do not see a statistically significant effect of aging owners on value added.

In Column 4 I extend the model by controlling for one and two periods of lagged log-investments as well as log-employment. Apart from that the regression is the same as that displayed in Column 1. The remaining effect on value added after controlling for former investments and employment is a crude measure of the age effect on factor productivity. Ideally, I should have controlled for the level of capital rather than lagged investments. Unfortunately, the capital figures are negatively biased over time due to accounting rules on write-offs that do not correspond to the real rate of depreciation on capital. Therefore, as an alternative I control for lagged values of firm investments. For each additional lag I include I lose one time period in my regression. Thus, since my time series are limited in length, I am only able to control for a limited number of investment lags. In the regressions displayed in Table 4.3 I include two periods of lagged investments. The coefficient estimates are robust with regards to including more investment lags. Robustness tests also show that the most recent investment lags are the most important in order to estimate the effect on value added. While investments lagged one period increase current value added with about 3%, investments lagged four periods increase current value added with less than 1%.

From Column 4 we see that there is a negative effect on value added from owner age also when controlling for capital and labor inputs. The estimates are statistically different from zero for owners older than 65 years of age, although only at the 10% level for the owner age cohort 71–75. Comparing the estimates in Column 4 with the estimates in Column 1 gives us an understanding of how much of the negative age effect on value added comes from reduced factor inputs and how much is due to reduced factor productivity. For example, I find that the estimated effect from the owner age group 66 to 70 in Column 4 is about 40% of the total impact on valued added estimated for the same age cohort in Column 1. Thus, for this age group the point estimates suggest that 40% of the reduction of value added from aging owners is due to reduced productivity, while the remaining 60% is due to reduced factor inputs in the production.

Separating the downscaling effect from the productivity effect on value added is highly interesting because the two are likely to have different welfare implications. The decline in value added coming from aging owners and CEOs having fewer employees and reducing their capital expenditures need not involve any efficiency loss, but rather only imply a reallocation of resources from downscaling firms to growing firms with higher productivity. A reduction in value added coming from reduced productivity, however, involves a less efficient use of resources.

Interestingly, from Column 4 we also see that there seems to be a positive effect of firm productivity from transferring ownership. The point estimate is statistically significant at the 1% level and tells us that transferring ownership on average increases the productivity of the firm with 7.1% compared to the period before the transfer. Comparing the point estimate on ownership transfer in Column 4 with the same point estimate in Column 1 tells us that nearly 60% of the effect on value added from an ownership transfer is due to productivity, while 40% is due to increased factor inputs.

Controlling for CEO age, Column 5, none of the owner age estimates are significantly different from zero. In fact, most of the point estimates, except for owners at 70–75 years of age, are very close to zero. I do, however, find a statistically negative effect on firm value added from CEO age. The effect seems to start for CEOs older than 60 years of age. The negative effect does also seem to increase with the age of the CEO. Although the effect for CEOs between 70 and 75 years of age is negative, it is not statistically significant at the 10% level (p-value=0.14).

The results in Column 5 suggest that the aging of CEOs has an impact on firm productivity, while the aging of firm owners does not. The estimates in Column 5 are smaller than the estimates in Column 2. Again, this is natural as I control for the effect on value added due to changes in factor inputs. Comparing the point estimates in Column 2 and Column 5 suggests that about half of the negative effect on value added from CEOs between 66 and 70 years of age is due to reduced productivity, while for CEOs older than 75 years of age more than 70% is due to reduced productivity. Surprisingly, Column 5 also shows that there does not seem to be any effect on productivity from changing the CEO. In Column 6 I also control for the aging of the firm owner when the owner is also the CEO. I do not find an additional age effect on firm productivity of the owner also being the firm's CEO. Adding this extra control has little effect on the estimates as they were presented in Column 5. The estimate for CEOs at ages between 61 to 65 is, however, no longer statistically significant at the 5% level.

TABLE 4.3:
Estimated effects on valued added of owner and CEO age.

	(1) Coef./SE	(2) Coef./SE	(3) Coef./SE	(4) Coef./SE	(5) Coef./SE	(6) Coef./SE
OwnerAge51to55	-.009	.034	.034	-.014	-.000	-.001
	(.01)	(.02)	(.02)	(.01)	(.02)	(.02)
OwnerAge56to60	-.038**	.015	.010	-.020	-.027	-.022
	(.02)	(.03)	(.03)	(.02)	(.03)	(.03)
OwnerAge61to65	-.089***	-.015	-.019	-.024	.009	.014
	(.02)	(.03)	(.03)	(.02)	(.03)	(.03)
OwnerAge66to70	-.196***	-.042	-.045	-.089***	.009	.014
	(.03)	(.04)	(.04)	(.03)	(.04)	(.04)
OwnerAge71to75	-.164***	-.067	-.070	-.096**	-.070	-.066
	(.04)	(.05)	(.05)	(.05)	(.06)	(.06)
OwnerAge> 75	-.248***	.032	.030	-.176***	.008	.011
	(.07)	(.07)	(.07)	(.07)	(.08)	(.08)
CEOAge51to55		-.058***	-.059***		-.018	-.018
		(.02)	(.02)		(.02)	(.02)
CEOAge56to60		-.079***	-.087***		.004	.014
		(.02)	(.03)		(.03)	(.03)
CEOAge61to65		-.128***	-.138***		-.064**	-.051*
		(.03)	(.03)		(.03)	(.03)
CEOAge66to70		-.321***	-.331***		-.176***	-.163***
		(.04)	(.04)		(.04)	(.04)
CEOAge71to75		-.249***	-.259***		-.098	-.086
		(.07)	(.07)		(.07)	(.07)
CEOAge> 75		-.753***	-.760***		-.536***	-.525***
		(.10)	(.10)		(.11)	(.11)
Owner-CEOAge> 55			.017			-.020
			(.02)			(.02)
OwnershipTransfer	.121***	.122***	.122***	.075***	.072***	.072***
	(.02)	(.02)	(.02)	(.02)	(.03)	(.03)
CEOChange		.057***	.058***		.017	.016
		(.02)	(.02)		(.02)	(.02)
ln(l.Investment)				YES	YES	YES
ln(l2.Investment)				YES	YES	YES
ln(Employees+1)				YES	YES	YES
FirmAge(d)	YES	YES	YES	YES	YES	YES
Year(d)*Industry(d)	YES	YES	YES	YES	YES	YES
F-value	74.06	55.84	54.17	40.31	32.83	32.75
R-squared	.0134	.017	.017	.1846	.1875	.1875
No. of obs.	165,923	125,955	125,953	115,167	85,398	85,396

Note: This table reports the estimated effect on log-value added on a panel data set covering the years 2000 to 2009. The independent variables of the regression model are the same as described in Equation 4.1, except that the time dummies are industry specific. The estimates are derived applying fixed effect estimation. See Table C.7 for variable definitions. Standard errors are reported in parentheses: * significance at ten, ** five, *** one percent.

4.5 Robustness tests

4.5.1 Investment spikes

In Section 4.4.1 I found evidence suggesting that the aging of firm owners and CEOs has a negative effect on the level of firm investments. Empirical evidence suggests that firm investments are made in time concentrated lumps, see e.g. Nilsen et al. (2009). This may suggest that the binary decision whether to invest is just as relevant as how much to invest. Thus, as a robustness test, I also investigate whether the probability of the decision to invest is affected by the age of owners and CEOs.

Small firms, measured by capital stock, have more volatile investment ratios. Thus, the probability of a small firm having an investment ratio over a certain fixed threshold is higher than for large firms. In order to control for this the definition of an investment spike should depend on the size of the capital stock.

Following the method applied by Nilsen et al. (2009), I define the value of the expected investment-capital ratio contingent on the size of the capital stock the period before as $\mu(K_{i,t-1}) \equiv E[I_{i,t}/K_{i,t-1}|K_{i,t-1}]$. Since my investment figures include capital sales the investment ratio can be negative. I handle this by left censoring all negative investment figures to zero. Then I estimate the conditional expected value of the investment ratio by running the following regression: $\mu(K_{i,t-1}) = \beta_0 + \beta_1 ln(K_{i,t-1})$. This estimate of $\mu(K_{i,t-1})$ can also be negative. Similar to Nilsen et al. (2009) I therefore set the lower threshold of a spike equal to 20%. Consequently my definition of an investment spike is:

$$S_{i,t} = \begin{cases} 1 & \text{if } I_{i,t}/K_{i,t-1} > max[\alpha\mu(K_{i,t-1}), 0.20] \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

Using the same combined rule for investment spikes as Nilsen et al. (2009), I get relatively similar results with respect to the share of investments defined as spikes, while I find that a larger share of total investments are made during spikes. That their share of investment is lower than my estimates can partly be explained by the fact that a larger share of my observations are defined as spikes, 13% compared to 9%. Nilsen et al. (2009) also include operational leasing in their investment figures which reduce the share of capital invested during spikes. Moreover, my investment figures are net of capital sales. Thus, in my data set, investments are set equal to zero if the level of capital sales is larger than investment expenditures. This may be the case for many of the smaller investments. In fact, 17% of the observations in the data set are set equal to zero because the firm has a higher level of asset sales than investment expenditures.

Figure C.2 in Appendix C.1 shows the share of firms with an investment spike as a function of owner age, CEO age, owner-CEO age and firm age, respectively. The figure shows a clear tendency towards a decreasing share of firms with an investment spike as the owner becomes older (top left corner), the CEO becomes older (bottom left corner) as well as owner-manager aging (top right corner). Since there are few observations in the left and right tails of the age distribution it is natural that the spike ratios are more volatile here. Interestingly, we see that the investment ratio is stable, or even increasing, with respect to firm age (bottom right corner). The latter finding is surprising taking into consideration that firm age is positively correlated with age of the firm owner and the CEO.

I investigate the pattern further by running regressions with the investment spike variable as the dependent variable. The results are shown in Table C.4 in Appendix C.1. The right hand side variables are the same as in Equation 4.1 in Section 4.4.1. The fixed effect logit model is applied as estimator. The estimated coefficients can be interpreted as investment spike log-odds ratios. A negative value means that the probability of the firm having an investment spike is decreasing with the respective variable. In the analyses I use three different threshold values for an investment to be categorized as a spike.

For the minimum threshold 0.1, Column 1-3, we see that the estimated effect of aging owners and CEOs on the probability of having an investment spike follows a similar pattern as the estimated age effect on firm investment displayed in Table 4.1. In fact, the estimated effect of owner age on the likelihood of the firm having an investment spike has a higher statistical significance than the owner age effect on the amount of investments. The results suggest that it is not only the amount of investments that is affected by aging owners and CEOs, but also the frequency of conducting larger investments.

For the minimum investment spike thresholds 0.2 and 0.3, respectively, see Table 4.2, we see that the results are relatively robust compared to Column 1–3. The frequency of larger investment spikes does, however, seem less affected by owner and CEO age than smaller spikes. Particularly, although the point estimates are negative, the reduced likelihood of the firm having an investment spike is only statistically significant for the oldest owners and CEOs.

4.5.2 Firm size and the effect of age on productivity

As a robustness test, this section investigates whether the negative effect on firm productivity from aging CEOs holds also for larger firms. If the result does not hold for larger firms then this implies that the negative effect on productivity of aging CEOs is limited to firms where the CEO is a large share of the firm's total employees. This type of effect could be interpreted as similar to the effect from aging employees, rather than a specific effect from aging CEOs.

I test the importance of firm size by running several regressions gradually increasing the firm size threshold for entering the sample. The results are displayed in Table C.5. For example, the regression displayed in Column 1 includes firms with two or more employees in one or more years during the period 2000 to 2009, while the regression displayed in Column 2 includes firms with four or more employees in one or more years during the period 2000 to 2009. The regression model is the same as the regression displayed in Table 4.3 Column 6.

To make it easy to compare results, the regression results from Table 4.3 Column 6 are replicated in Table C.5 Column 1. Increasing the minimum number of employees gradually up to ten, see Column 2–4, the regression results on productivity are very stable compared to the previous results, see Column 1. For firms with 10 or more employees, see Column 4, there are indications of a negative effect from owner age on productivity. The results do, however, not seem very robust. For example, for firms with 10 or more employees there is a statistically significant positive effect from firm owners older than 75 years of age, while for firms with more than 20 employees, the point estimate is exactly the same only with the opposite sign. For firms with 20 or more employees, see Column 5, I do no longer find a statistically significant effect on productivity of CEO age. The point estimates for CEOs at ages between 61 and 70 year are, however, still very similar. One should keep in mind that the sample containing firms with 20 employees or more is only one sixth of the full sample. Thus, it could be that the point estimates lose significance due to fewer observations. As an additional robustness of whether the age effect is valid for larger firms I run a regression on the full sample interacting the CEO age dummy variables with a dummy variable for whether the firm has had 20 or more employees during the period. I do not find statistically significant differences between the CEO age effect for small and large firms. However, although not statistically significant, the trend seems to be that the effect of CEO age is smaller for larger firms.

Column 6 displays the results of a regression including only firms with less than 20 employees in one or more years during the period 2000 to 2009. Again, the results are very similar as displayed in Column 1–3.

4.6 Welfare effects of aging owners and CEOs

The results presented in Section 4.4.3 suggest that the decrease in value added from aging CEOs is partly due to reduced factor inputs, and partly due to reduced productivity in firms led by aging CEOs.

A decline in firm value added due to fewer employees and less capital suggests a reallocation of resources, possibly to other firms where it can be put into alternative productive use. Whether the reduction in factor inputs leads to an efficiency loss for the economy will depend on the efficiency of the labor and capital markets. If the previous employees end up in redundancy due to the downscaling, then this will be an efficiency loss for the economy, at least in the short run. The rate of long term unemployed in Norway has been low during this period. This suggests that the downscaling effect has not led to a considerable efficiency loss for Norway. However, for other economies, with similar demographics and a less dynamic labor market, the downscaling of employees and capital may lead to a poorer utilization of resources.

The reduction in value added due to lower productivity in firms run by aging CEOs, however, is most likely to be negative for welfare. I calculate the aggregate productivity loss due to aging CEOs to be 4.9 billion NOK (EUR 0.6 bn.) per annum. This amounts to 0.2% of Norway's mainland GDP in 2013. The details of the calculations are displayed in Table 4.4. Starting with Column 1, we see the estimated productivity effects of aging CEOs from Section 4.4.3 Table 4.3 Column 6. The CEO age cohort estimates that are not statistically significant different from zero at the 5% level are set equal to zero. Column 2 displays the average firm value added per 2013 for all Norwegian firms by CEO age cohort.[4] In Column 3 I calculate the average counterfactual value added had the firm not been exposed to a negative CEO age effect. The counterfactual value added is calculated by dividing the actual value added figure, see Column 2, by 1 plus the estimated CEO age effect in Column 1. Subtracting the actual value added in Column 2 from the counterfactual value added in Column 3 we find the average productivity loss due to the negative CEO age effect on value added, see Column 4. The total productivity loss, Column 6, is calculated by multiplying the average firm productivity loss, Column 4, with the total number of firms per CEO age cohort, Column 5.

We see from Table 4.4 Column 6 that the aggregated negative effect on value added is largest for CEOs between 66 and 70 years of age. The average productivity loss for firms managed by CEOs in this group is 2.4 million NOK (EUR 0.3 mill.), which adds up to a total of 4 billion NOK (EUR 0.5 bn.). In comparison, the average productivity loss for

[4]The value added figures are based on a sample containing all Norwegian limited liability firms, foundations and cooperatives with two or more employees and one million kroner or more in labor costs.

TABLE 4.4: Productivity effect for Norway of aging CEOs.

	Firm average				Total	
	(1)	(2)	(3)	(4)	(5)	(6)
Age	**Estimate**	**Value added**	**Counterfactual**	**Loss**	**No. firms**	**Loss**
51 – 55	0.000	29.7	29.7	0.0	9,565	0
56 – 60	0.000	40.4	40.4	0.0	7,443	0
61 – 65	0.000	15.5	15.5	0.0	4,555	0
66 – 70	-0.163	12.3	14.6	-2.4	1,665	-3,973
71 – 75	0.000	6.8	6.8	0.0	345	0
> 75	-0.525	8.3	17.5	-9.2	101	-929
Total					56,941	-4,902

Note: The estimates in Column 1 can be interpreted as percentage points. Nominal amounts are in million Norwegian 2013-kroner. The average counterfactual value added per firm is calculated by dividing the factual value added figure, Column 2, by one plus the age cohort point estimate, Column 1. The total productivity loss, Column 6, is calculated by multiplying the average firm productivity loss, Column 4, with the total number of firms per CEO age cohort, Column 5.

firms with CEOs older than 75 years of age is estimated to be 9.2 million NOK (EUR 1.2 mill.). However, since there are relatively few firms with CEOs older than 75 years of age, the total productivity loss is only 0.9 billion NOK (EUR 0.12 bn.).

There is uncertainty related to these estimates. Using the standard errors of the point estimates for each CEO age cohort reported in Table 4.3 Column 6 I calculate the 95% confidence interval for each CEO age cohort. Summing the minimum and maximum value for each age cohort I find that the aggregate productivity effect of aging CEOs per year is somewhere between -0.1% and -0.4% of Norwegian mainland GDP.

My calculation of the aggregate productivity loss is based on the assumption that the negative effect from aging CEOs is the same for small and large firms. Whether or not there exists a negative CEO effect also for the largest firms will have a great impact on the aggregate productivity effect. One could expect larger firms to have a more professionalized company board detecting and reacting promptly if the CEO is not managing the firm optimally. In fact, although the point estimate for CEOs between 66 and 70 years of age is at the same level for the sample of firms with 20 employees or more as for firms with less than 20 employees, see Table C.5 Column 5, it is not statistically significant. Performing a similar calculation as displayed in Table 4.4 for firms with less than 20 employees, see Table C.6 Column 6 in appendix, the aggregate productivity loss per year is 1.7 billion NOK (EUR 0.2 bn.). This amounts to 0.07% of Norwegian mainland GDP. Thus, assuming that there is no CEO age productivity effect on firms with 20 employees or more, the aggregate productivity effect is reduced to one third of the aggregate effect estimated in Table 4.4.

A relevant question arising from this analysis is; why do we observe these results? Why do firms not boost their productivity simply by replacing older managers with younger ones? Running a fixed effect regression on the data set I find a statistically significant reduction in CEO pay with CEO age. Hence, part of the CEOs negative productivity effect is captured by lower wage earnings. The CEO pay effect, however, only compensates for a small part of the negative productivity effect on firm performance.

One explanation for why owners do not replace their aging CEO despite a negative productivity effect is that a large share of firm owners only look for potential succeeding owners and managers among their close family. This in turn reduces the pool of potential management talent and the potential for a good match (Bennedsen et al., 2006). Moreover, even if the owner is willing to look for alternatives outside the family, there is likely to be a matching problem with respect to recruiting a manager with the right profile. This is analogous to matching problems in labor markets in general (see e.g. Mortensen and Pissarides (1999)), but perhaps particularly challenging in the sub market of management talent.

An other type of explanation is that older incumbent CEOs can be reluctant to leave their position. Being the CEO of a firm is normally associated with influence and recognition and is likely to be an important part of the person's identity. Thus, aging managers may want to postpone retiring as long as possible even if this may have negative consequences for the firm.

Is it possible to say anything about the policy implications of these results? Assuming that there exists a potential policy that facilitates the replacement of older incumbent CEOs with younger and more productive colleagues, would it be welfare enhancing to implement such a policy? The answer to this depends to a large extent on the size of the firm and the outside options of the incumbent CEO. If retirement is the most favorable alternative of the CEO, then everything equal, this will have a negative impact on society as the workforce is reduced. The older the CEO, the more likely it is that retirement is the preferred outside option. While the larger the firm in question the larger is also the potential negative productivity effects of an aging CEO. It is in the intersection of these two effects that we find the firms for which it would be welfare enhancing to replace the incumbent CEO.

As an example, let us consider a policy that aims at replacing CEOs in the age group 66–70. The average pay for this CEO age group is 437 000 NOK (EUR 55 000) per year. The isolated negative effect on value added of the CEO going into retirement is equal to his pay of 437 000 NOK. Thus, a policy that would replace the incumbent CEO would be socially optimal if the CEO's pay is smaller than the firm's productivity loss of having an older CEO. A back of the envelope calculation suggests that this type of policy would be socially profitable for firms with a value added of 2 700 000 (EUR 335 000) or more. If you subtract 16.3% from 2 700 000, the estimated negative effect on productivity of CEOs in the age group 66–70, you get the average CEO's pay. In comparison, the average contra factual value added for firms managed by CEOs in this age group is 14.6 million NOK (EUR 1.8 mill.), and the average productivity 2,4 million NOK per firm, see Table 4.4. Thus, the results suggest that it is on average welfare enhancing to replace CEOs in this age group with younger individuals. The result also holds if we only focus on firms with less than 20 employees. The analysis does, however, not say anything about whether such young alternative CEOs exists, or the size of administration costs (and other potential costs) related to such a policy.

4.7 Conclusion

I find that the age of firm owners and CEOs has a negative impact on the level of firm investments and firm employment. I find a statistically significant negative effect on firm employment from CEO age starting at ages between 51 and 55. The negative effect on investments from CEO age seems to start five years later, suggesting that the firm level decline in employment leads the decline in investment activity. For aging owners I identify a negative effect on the amount of firm investment for owners older than 60 years of age. The point estimate is, however, only statistically significant for owners between 71 and 75 years of age. Running a robustness test on the likelihood of the firm having an investment spike, I do, however, find evidence suggesting that owner age has a statistically significant negative effect on the likelihood of the firm conducting larger investment projects. For employment I find a negative effect of owner age on employment for owners older than 65 years of age. The effect is, however, only statistically significant for firm owners between 66 and 70 years of age. The results are robust controlling for firm level fixed effects, ownership transfers, change of CEO as well as firm age and business cycles.

Controlling for factor inputs I find a statistically significant negative effect from CEO age on value added. This result suggests that there is a reduction in firms' productivity as the CEO becomes older. The effect seems to start for CEOs older than 60 years of age. The negative effect does also seem to increase with the age of the CEO. Conducting robustness tests with respect to firm size I do not find a statistical significant effect on productivity for firms with more than 20 employees. The CEO age effect for firms with more than 20 employees is, however, not statistically significant different from that of smaller firms. I do not find any statistically significant effects from owner age on firm value added or productivity. This, may suggest that the owner's competencies do not deteriorate with age.

I also test whether there is an additional age effect when the owner and the CEO are the same individual. I do not find a statistically significant effect on investments, employment or productivity. These results suggest that having decision and management control concentrated with the same individual does not give an additional negative age effect.

Based on the regression results I calculate the annual aggregate productivity loss effect due to aging CEOs to amount to 0.2% of Norwegian mainland GDP. The estimate is highly uncertain. Particularly, if there is no CEO age effect on larger firms with more than 20 employees, the effect is only one third of that estimated for the entire sample (0.07% of Norwegian mainland GDP).

Why firms do not adjust to the negative productivity effects by replacing unproductive CEOs, and whether it would be welfare improving to implement a policy aiming at replacing aging incumbent CEOs with younger and more productive colleagues, remain open questions. Back of the envelope calculations suggest that there are potential positive welfare effects from replacing aging CEOs. The size of these effects will depend on the size of the firm and the outside option of the incumbent CEO. The larger the firm, the larger is the potential welfare benefit from replacing an unproductive CEO. In contrast, if the CEO is likely to retire if not working as a CEO, the welfare effects are smaller. This suggests that potential policy measures should not be directed towards small firms where the CEO does not have productive outside options.

References

Bakshi, G. S. and Z. Chen (1994). Baby boom, population aging and capital markets. *Journal of Business 67*(2), 165–202.

Bennedsen, M., K. M. Nielsen, F. Pérez-González, and D. Wolfenzon (2006). Inside the family firm: The role of families in succession decisions and performance. Technical report, National Bureau of Economic Research.

Berglann, H., E. R. Moen, K. Røed, and J. F. Skogstrøm (2011). Entrepreneurship: Origins and returns. *Labour Economics 18*(2), 180–193.

Cooley, T. F. and V. Quadrini (2001). Financial markets and firm dynamics. *American Economic Review 91*(5), 1286–1310.

Cucculelli, M. and G. Micucci (2007). Estimating age effect in entrepreneurship and business.

Ebner, N. C., A. M. Freund, and P. B. Baltes (2006). Developmental changes in personal goal orientation from young to late adulthood: From striving for gains to maintenance and prevention of losses. *Psychology and Aging 21*(4), 664–678.

Engel, D., T. Bauer, K. Brink, S. Down, J. Hartmann, L. Jacobi, T. Kautonen, L. Trettin, F. Welter, and J. Wiklund (2007). Unternehmensdynamik und alternde bevölkerung.

European Commission (2002). Final report of the expert group on the transfer of small and medium-sized enterprises.

European Commission (2006). Transfer of businesses - continuity through a new beginning.

European Commission (2011). Business dynamics: Start-ups, business transfers and bankruptcy.

Evans, D. (1987). The relationship between firm growth, size, and age: Estimates for 100 manufacturing industries. *Journal of Industrial Economics 35*(4), 567–581.

Fama, E. F. and M. C. Jensen (1983). Separation of ownership and control. *Journal of Law and Economics 26*(2), 301–325.

Goyal, V. K. and C. W. Park (2002,). Board leadership structure and CEO turnover. *Journal of Corporate Finance 8*(1), 49 – 66.

Grünfeld, L. and E. Jakobsen (2006). *Hvem Eier Norge? Eierskap og verdiskaping i et grenseløst næringsliv*. Universitetsforlaget.

Habib, M. A., U. Hege, and P. Mella-Barral (2013). Entrepreneurial spawning and firm characteristics. *Management Science 59*(12), 2790–2804.

Kautonen, T., S. Down, and M. Minniti (2014). Ageing and entrepreneurial preferences. *Small Business Economics 42*(3), 579–594.

Levesque, M. and M. Minniti (2006). The effect of aging on entrepreneurial behavior. *Journal of Business Venturing 21*(2), 177–194.

Loderer, C. F. and U. Waelchli (2010). Firm age and performance. *Available at SSRN 1342248*.

Lundstrum, L. L. (2002). Corporate investment myopia: A horserace of the theories. *Journal of Corporate Finance 8*(4), 353–371.

Marshall, J. P., R. Sorenson, K. Brigham, E. Wieling, A. Reifman, and R. S. Wampler (2006). The paradox for the family firm CEO: Owner age relationship to succession-related processes and plans. *Journal of Business Venturing 21*(3), 348–368.

Miller, L. J., A. Myers, L. Prinzi, and W. Mittenberg (2009). Changes in intellectual functioning associated with normal aging. *Archives of clinical neuropsychology 24*(7), 681–688.

Morin, R. and A. F. Suarex (1983). Risk aversion revisited. *The Journal of Finance 38*(4), 1201–1216.

Mortensen, D. T. and C. A. Pissarides (1999). New developments in models of search in the labor market. *Handbook of labor economics 3*, 2567–2627.

Neuberger, D. and S. Räthke-Döppner (2014). The role of demographics in small business loan pricing. *Small Business Economics*, 1–14.

Nilsen, Ø. A., A. Raknerud, M. Rybalka, and T. Skjerpen (2009). Lumpy investments, factor adjustments, and labour productivity. *Oxford Economic Papers 61*(1), 104–127.

Nunes, P., M. Goncalves, and Z. Serrasqueiro (2013). The influence of age on SMEs' growth determinants: Empirical evidence. *Small Business Economics 40*(2), 249–272.

Pålsson, A. (1996). Does the degree of relative risk aversion vary with household characteristics? *Journal of economic psychology 17*(6), 771–787.

Parker, S. C. (2009). *The economics of entrepreneurship.* Cambridge University Press.

Salthouse, T. A. (2009). When does age-related cognitive decline begin? *Neurobiology of aging 30*(4), 507–514.

Salthouse, T. A. (2014). Why are there different age relations in cross-sectional and longitudinal comparisons of cognitive functioning? *Current directions in psychological science 23*(4), 252–256.

Schumpeter, J. (1934). *The theory of economic development.* Harvard University Press.

Serfling, M. A. (2012). CEO age, underinvestment, and agency costs. *Eller College of Management, University of Arizona*.

Stuart-Hamilton, I. (2012). *The psychology of ageing: An introduction.* Jessica Kingsley Publishers.

Verhaegen, P. and T. A. Salthouse (1997). Meta-analysis of age-cognition reactions in adulthood. Estimates of linear and nonlinear age effects and structural models. *Psychological Bulletin 122*(3), 231–249.

Verhaeghen, P. and J. Cerella (2002). Aging, executive control, and attention: a review of meta-analyses. *Neuroscience and Biobehavioral Reviews 26*(7), 849 – 857.

Waelchli, U. and J. Zeller (2013). Old captains at the helm: Chairman age and firm performance. *Journal of Banking & Finance*.

Appendix A

Appendix to Chapter 2

A.1 Summary statistics, robustness tests and variable definitions

TABLE A.1:
Firm characteristics.

variable	mean	sd	p25	p50	p75	N
1-10 employees						
DummyLoan	0.27	0.45	0.00	0.00	1.00	75,946
MarketShare	0.17	0.20	0.05	0.07	0.18	75,946
OperatingMargins	0.01	0.44	-0.02	0.04	0.14	74,043
FirmAge	11.48	10.89	4.00	9.00	16.00	75,946
Loan	1,305	26,904	0	0	75	75,946
SecurityAssets	9,957	643,900	496	1,324	3,294	75,946
Sales	7,446	63,560	1,218	3,031	6,769	75,946
AltCredit	1,371	116,552	0	0	0	75,946
Employees	4	3	1	3	5	75,946
NewspaperSub.	0.96	0.23	0.81	0.84	1.11	75,899
11-20 employees						
DummyLoan	0.39	0.49	0.00	0.00	1.00	11,443
MarketShare	0.13	0.19	0.02	0.05	0.11	11,443
OperatingMargins	0.02	0.22	0.00	0.03	0.08	11,413
FirmAge	14.82	12.87	6.00	13.00	20.00	11,443
Loan	3,389	56,270	0	0	842	11,443
SecurityAssets	66,153	4,389,807	3,098	6,216	12,104	11,443
Sales	31,900	116,628	10,143	17,528	31,312	11,443
AltCredit	2,249	89,490	0	0	0	11,443
Employees	15	3	12	14	17	11,443
NewspaperSub.	0.95	0.23	0.80	0.84	1.10	11,438
21-50 employees						
DummyLoan	0.40	0.49	0.00	0.00	1.00	7,039
MarketShare	0.10	0.16	0.01	0.04	0.11	7,039
OperatingMargins	0.02	0.22	0.00	0.04	0.08	7,025
FirmAge	16.83	15.35	7.00	14.00	22.00	7,039
Loan	9,327	134,893	0	0	1,929	7,039
SecurityAssets	118,167	4,011,760	7,321	15,004	30,709	7,039
Sales	80,957	416,628	21,313	38,737	71,683	7,039
AltCredit	12,126	295,014	0	0	0	7,039
Employees	31	8	24	29	36	7,039
NewspaperSub.	0.93	0.22	0.80	0.84	1.08	7,032

Note: The table displays descriptive statistics dependent on firm size for the full cross section sample of firms per 2011. All nominal amounts are in 1,000 NOK. Variables are defined in Table A.9.

Table A.2:
Firm characteristics. Sample of firms without mother company or subsidiaries.

variable	mean	sd	p25	p50	p75	N
1-10 employees						
DummyLoan	0.28	0.45	0.00	0.00	1.00	55,373
MarketShare	0.17	0.21	0.05	0.07	0.18	55,373
OperatingMargins	0.04	0.40	-0.01	0.05	0.15	54,042
FirmAge	11.49	10.65	4.00	9.00	16.00	55,373
Loan	794	11,964	0	0	88	55,373
SecurityAssets	6,098	611,277	431	1,094	2,569	55,373
Sales	5,258	50,046	1,113	2,602	5,527	55,373
AltCredit	117	8,529	0	0	0	55,373
Employees	3	2	1	2	5	55,373
NewspaperSub.	0.96	0.24	0.81	0.86	1.12	55,342
11-20 employees						
DummyLoan	0.42	0.49	0.00	0.00	1.00	5,666
MarketShare	0.14	0.19	0.02	0.05	0.12	5,666
OperatingMargins	0.03	0.17	0.00	0.03	0.08	5,658
FirmAge	14.32	12.50	6.00	12.00	20.00	5,666
Loan	1,945	43,426	0	0	917	5,666
SecurityAssets	15,029	322,683	2,474	4,933	8,843	5,666
Sales	22,984	57,272	8,467	14,633	25,058	5,666
AltCredit	152	3,533	0	0	0	5,666
Employees	14	3	12	14	16	5,666
NewspaperSub.	0.95	0.23	0.81	0.85	1.10	5,666
21-50 employees						
DummyLoan	0.45	0.50	0.00	0.00	1.00	2,470
MarketShare	0.10	0.16	0.01	0.04	0.11	2,470
OperatingMargins	0.03	0.18	0.00	0.03	0.08	2,466
FirmAge	16.12	16.26	7.00	14.00	21.00	2,470
Loan	5,079	55,423	0	0	2,428	2,470
SecurityAssets	172,387	6,668,543	5,314	10,828	20,404	2,470
Sales	46,321	149,801	15,412	28,472	50,333	2,470
AltCredit	10,854	389,773	0	0	0	2,470
Employees	29	8	23	27	34	2,470
NewspaperSub.	0.93	0.22	0.80	0.84	1.07	2,468

Note: The table displays descriptive statistics for the 2011 cross section sub sample of independent firms without either mother company or subsidiaries. Comparing the statistics with the full sample statistics the sample characteristics are quite stable. This indicates that excluding firms with mother company or subsidiaries should have little or no impact on my regression results. All nominal amounts are in 1,000 NOK. Variables are defined in Table A.9.

Table A.3:
Firm and portfolio characteristics. Personally majority owned firms.

variable	mean	sd	p25	p50	p75	N
No. firms same municipality	1.9	3.0	1.0	1.0	2.0	77,725
No. firms same municipality ex. fin.	1.6	2.3	1.0	1.0	2.0	77,725
No. firms total	2.5	5.8	1.0	1.0	2.0	77,725
No. firms total ex. fin.	2.1	4.5	1.0	1.0	2.0	77,725
AgeOwner	51.0	10.7	43.0	51.0	59.0	77,725
FirmLoan	1,162	23,902	0	0	0	77,725
PortfolioLoan	23,483	271,915	0	0	685	77,725
PortfolioLoan (ex. fin.)	15,596	176,062	0	0	295	77,725
FirmSales	8,054	42,594	11	1,450	5,424	77,725
PortfolioSales	47,980	344,583	405	2,768	10,817	77,725
PortfolioSales (ex. fin.)	51,119	377,290	467	2,891	11,279	77,725
OwnerBankruptcy	0.002	0.046	0.000	0.000	0.000	77,725
NewspaperSub.	0.95	0.23	0.81	0.84	1.11	77,693

Note: The table displays firm and portfolio characteristics on the 2011 cross section sample of firms with a single personal majority owner. Portfolio characteristics are interesting because the community bank is likely to gain information about the firm's ability to handle a loan by observing other firms in the owner's portfolio. The table tells us that the median firm owner only has one portfolio company, while the mean firm owner has 2.5 firms in his portfolio. The mean firm owner has 1,9 firms located in the same municipality. All nominal amounts are in 1,000 NOK. Variables are defined in Table A.9.

Table A.4:
Community banks' effect on the probability of having loan from a credit institution (robustness test).

	(1) Full sample Coef./SE	(2) Excl. subsidiaries Coef./SE	(3) Personal majority Coef./SE
MarketShare (1-10 emp.)	.083***	.088***	.082***
	(.02)	(.02)	(.02)
MarketShare (11-20 emp.)	.088***	.070*	.074**
	(.03)	(.04)	(.04)
MarketShare (21-50 emp.)	.160***	.169***	.191***
	(.05)	(.05)	(.06)
ln(Employees)	.070***	.050***	.082***
	(.01)	(.01)	(.01)
ln(Employees)^2	-.018***	-.014***	-.022***
	(.00)	(.00)	(.00)
ln(SecurityAssets)	.035***	.037***	.023***
	(.00)	(.00)	(.00)
ln(Sales)	.013***	.033***	.035***
	(.00)	(.00)	(.00)
FirmAge (6-10)	.023***	.017***	.025***
	(.01)	(.01)	(.01)
FirmAge (11-20)	.015**	.001	.016**
	(.01)	(.01)	(.01)
FirmAge (>20)	.001	-.020*	-.007
	(.01)	(.01)	(.01)
ln(AltCredit)	-.006***	-.008***	-.001
	(.00)	(.00)	(.00)
OperatingMargin	-.022***	-.052***	-.051***
	(.01)	(.01)	(.01)
NewspaperSubscription	.045*	.036	.030
	(.02)	(.02)	(.02)
OwnerBankruptcy			.034
			(.07)
OwnerAge	NO	NO	YES
Industry (2-digit NACE)	YES	YES	YES
Centrality (1-5)	YES	YES	YES
Log-likelihood	-49092	-32463	-25249
Chi-Square	22831	14495	10931
No. of obs.	90078	60434	45046

Note: This table reports the marginal effects at means from estimating a probit model on a 2011 cross section data set. All variables are defined in Table A.10. To address the potential problem of reverse causality the most peripheral municipalities (65 out of a total of 428) are excluded from the samples. See Table 2.1 for further description of the regression model and firm samples. Cluster robust standard errors (SE) at the municipality level are reported in parentheses: * significance at ten, ** five, *** one percent.

Table A.5: Community banks' effect on the amount of credit financing (robustness test).

	(1) Full sample Coef./SE	(2) Excl. subsidiaries Coef./SE	(3) Personal majority Coef./SE
Long term debt credit institution			
MarketShare (1-10 emp.)	.953***	.758***	.779***
	(.15)	(.10)	(.16)
MarketShare (11-20 emp.)	1.130***	.841***	.883***
	(.25)	(.19)	(.26)
MarketShare (21-50 emp.)	1.375***	1.088***	1.314***
	(.38)	(.35)	(.48)
ln(Employees)	.425***	.020	.312**
	(.14)	(.07)	(.14)
$\ln(\text{Employees})^2$	-.095***	.010	-.073**
	(.03)	(.02)	(.04)
ln(security assets)	1.057***	.909***	.891***
	(.05)	(.03)	(.04)
ln(sales)	.033	.129***	.143**
	(.03)	(.03)	(.06)
ln(alt. non-equity finance)	-.021	-.017	.010
	(.02)	(.02)	(.02)
Operating margin	-.494***	-.550***	-.696***
	(.06)	(.06)	(.10)
NewspaperSubscription	.501***	.327***	.358***
	(.11)	(.07)	(.10)
Dummy owner bankruptcy			.247
			(.48)
OwnerAge	NO	NO	YES
Industry (A-V)	YES	YES	YES
Centrality (1-5)	YES	YES	YES
Mills			
lambda	4.006***	2.546***	3.143***
	(.66)	(.40)	(.66)
rho	1.00	1.00	1.00
sigma	4.01	2.55	3.14
No. of obs.	92,324	62,062	46,139

Note: This table reports the effect on long term loans from credit institution in a two-stage Heckman model. The outcome model estimates the following equation: $ln(LOAN_i) = \beta_1 MarketShare_{k,s} + \beta_2 CONTROLS + \beta_3 \lambda_i + u$. λ is the inverse Mills' ratio of firm i. λ is calculated based on the estimates from the probit model regressing the probability of having long term credit financing. This is referred to as Heckman's first step and is identical to the analysis displayed in Table 2.1. All variables are defined in Table A.10. Firm age is used as an exclusion criterion in the 2nd stage Heckman correction. See Table 2.2 for more on the regression model and data. Standard errors (SE) are reported in parentheses: * significance at ten, ** five, *** one percent.

Table A.6:
Characteristics community bank portfolio.

variable	mean	sd	p25	p50	p75	N
MarketShare	0.86	0.03	0.84	0.86	0.88	204
Centrality (1-5)	3.22	1.17	3.00	3.00	4.00	204
NewspaperSubscription	1.15	0.22	1.05	1.08	1.35	204
CreditRating	2.72	1.03	AA	A	A	204
Employees	5.75	6.32	2.00	3.00	8.00	204
Sales	7,097	11,991	1,367	3,408	7,324	204
Labor costs	1,642	2,200	387	925	2,052	204
ValueAdded	2,112	3,250	514	1,194	2,765	204
TotalAssets	3,518	7,043	695	1,573	3,700	204
Loan	1,095	1,936	194	436	1,165	204
SecurityAssets	2,721	5,490	485	1,166	2,599	204
OROA	0.14	0.21	0.02	0.13	0.25	204
OperatingMargin	0.04	0.19	-0.00	0.03	0.10	201
BankruptAfter	0.01	0.10	0.00	0.00	0.00	204
InactiveAfter	0.15	0.36	0.00	0.00	0.00	204
OperatingDeficitAfter	0.62	0.49	0.00	1.00	1.00	204
FirmAge	11.04	10.05	4.00	9.00	15.00	204

Note: The table displays summary statistics for the group of firms 1) located in a municipality with a community bank market share ≥ 0.8 and 2) received long term loan financing from a credit institution in the period 2004-2008 for the first time. The sample includes firms with 1-50 employees the year they received loan financing. Investment and real estate firms are excluded from the sample. All nominal amounts are in 1,000 NOK. Except for loan size, all variables are measured the year before treatment, which is the year the firms received long term credit financing from a credit institution for the first time. The credit rating is from Dun & Bradstreet, where AAA (given value 1) is the best and C (given value 5) is the worst. For example, an average rating of 2.5 is a rating in the middle between AA and A. Variables are defined in Table A.9.

Table A.7:
Characteristics non-community bank portfolio.

variable	mean	sd	p25	p50	p75	N
MarketShare	0.07	0.05	0.03	0.05	0.10	8,393
Centrality (1-5)	1.69	1.04	1.00	1.00	2.00	8,388
NewspaperSubscription	0.94	0.22	0.81	0.84	1.06	8,366
CreditRating	2.63	1.04	AA	AA	A	8,370
Employees	6.91	8.10	2.00	4.00	8.00	8,335
Sales	12,518	62,694	1,895	4,553	10,884	8,393
Labor costs	2,441	3,804	560	1,282	2,740	8,393
ValueAdded	3,376	21,307	712	1,606	3,519	8,393
TotalAssets	20,617	275,476	888	2,078	5,207	8,393
Loan	5,729	95,746	200	460	1,349	8,393
SecurityAssets	8,862	126,108	659	1,581	4,090	8,393
OROA	0.15	0.23	0.03	0.15	0.29	8,381
Operating margins	0.04	0.19	0.00	0.05	0.11	8,255
BankruptAfter	0.01	0.12	0.00	0.00	0.00	8,393
InactiveAfter	0.19	0.39	0.00	0.00	0.00	8,393
OperatingDeficitAfter	0.59	0.49	0.00	1.00	1.00	8,393
Firm age	10.73	10.99	4.00	8.00	15.00	8,392

Note: The table displays summary statistics for the group of firms 1) located in a municipality with a community bank market share ≤ 0.2 and 2) received long term loan financing from a credit institution in the period 2004-2008 for the first time. The sample includes firms with 1-50 employees the year they received loan financing. Investment and real estate firms are excluded from the sample. All nominal amounts are in 1,000 NOK. Except for loan size, all variables are measured the year before treatment. Variables are defined in Table A.9.

TABLE A.8:
Activity, growth and profitability for firms with community bank credit versus firms with alternative long term credit.

	(1) Active Coef./SE	(3) Deficit Coef./SE	(4) ln(sales+1) Coef./SE	(5) ln(va+1) Coef./SE	(6) ln(employees+1) Coef./SE	(7) OM Coef./SE	(8) ln(Debt+1) Coef./SE
Treated		.060*	-.001	.009	-.080	.000	-.001
		(.04)	(.04)	(.03)	(.06)	(.02)	(.03)
After		.057***	.273***	.225***	.163***	-.028***	.502***
		(.01)	(.01)	(.01)	(.01)	(.00)	(.01)
Treated*After	.005	-.015	-.074	-.127***	.010	.014	.007
	(.01)	(.03)	(.08)	(.04)	(.11)	(.02)	(.12)
ln(Loan)	YES	YES	YES	YES	YES	YES	YES
ln(Sales l.treat)	YES	YES	YES	YES	YES	YES	YES
ln(LaborCosts l.treat)	YES	YES	YES	YES	YES	YES	YES
YearTreatment	YES	YES	YES	YES	YES	YES	YES
FirmSize	YES	YES	YES	YES	YES	YES	YES
FirmAge	YES	YES	YES	YES	YES	YES	YES
Industry (A-V)	YES	YES	YES	YES	YES	YES	YES
Centrality (1-5)	YES	YES	YES	YES	YES	YES	YES
Estimation method	Probit	Probit	Probit	OLS	OLS	OLS	OLS
F-value			2760.98	6104.50	1851.74	17.20	165.69
R-squared			.76	.66	.64	.04	.19
Log-likelihood	-2,403	-17,939	-26,370	-23,785	-24,571	2,146	-29,223
Chi-Square	798	1,068					
N	22,148	32,142	32,140	31,799	32,128	31,605	32,142

Note: This table compares the performance of firms with credit from a community bank versus firms with credit from other credit institutions. While Column 1–2 only investigate post-treatment differences, the regressions displayed in Column 3–8 have a difference-in-differences setup. The main explanatory variable of interest is the interacted variable *Treated*After*, which is the difference in difference estimate. The sample contains only firms receiving long term credit financing for the first time during the time period 2004-2008. The treatment group contains firms located in municipalities with a community bank market share of 0.9 or more, while the control group is selected from municipalities with a community bank market share of less than 0.1. The panel covers a period of two years before and four years after treatment. The year of treatment is excluded from the regression. Control variables in the regression are the size of loan granted, sales one year before treatment, labor costs one year before treatment, industry affiliation (A-V), centrality (1-5), dummy for firm size and firm age. All variables are defined in Table A.10. The sample includes small firms with 1-50 employees. Cluster robust standard errors (SE) are reported in parentheses: * significance at ten, ** five, *** one percent.

Table A.9:
Definitions of variables in the descriptive statistics.

Variable	Definition
Dummy loan credit institution	Binary variable equal to one if the firm has long term loan financing from a credit institutition, and equal to zero otherwise.
MarketShare	Variable between zero and one depending on the market share for community banks in terms of number of loans in the municipality.
OperatingMargins	Firm operating results divided on firm sales. Winzorized at the top and bottom 2.5 percentiles.
FirmAge	Number of years since the firm was established.
Loan	The firm's amount of long term loan financing from a credit institution (1,000 NOK).
SecurityAssets	The firm's current assets and real estate. The amount of assets suitable as collateral security.
Sales	Firm sales (1,000 NOK).
AltCredit	The firm's amount of convertible loans, subordinated loan capital, loans to mother company and industry bonds.
Employees	Number of employees registered with the firm.
No. firms municipality	The number of firms in the municipality where the firm owner has a 10% owner stake or more.
No. firms municipality (ex. fin.)	The number of non-financial firms in the municipality where the firm owner has a 10% owner stake or more.
No. firms total	The total number of firms in Norway where the firm owner has a 10% owner stake or more.
No. firms total (ex. fin.)	The total number of non-financial firms in Norway where the firm owner has a 10% owner stake or more.
AgeOwner	The age of the majority owner of the firm.
FirmLoan	The firm's amount of long term loan financing from a credit institution (1,000 NOK).
PortfolioLoan	The amount of long term loan financing from a credit institution in the firm owner's portfolio (1,000 NOK).
PortfolioLoan (ex. fin.)	The amount of long term loan financing from a credit institution in the firm owner's portfolio of non-financial firms (1,000 NOK).
PortfolioSales	Sales of the firm owner's portfolio (1,000 NOK).
PortfolioSales (ex. fin.)	Sales of the firm owner's portfolio of non-financial firms (1,000 NOK).
OwnerBankruptcy	Binary variable equal to one if the owner of the firm has been involved in a bankruptcy in the same municipality.
CreditRating	Dun & Bradstreet credit rating. AAA=1, AA=2, A=3, B=4, C=5 and no rating=6.
ValueAdded	The firm's gross value added (sum of operating results, labor costs, write offs and write downs) (1,000 NOK).
TotalAssets	The firm's total assets (1,000 NOK).
OROA	The firm's operating results on assets. Winzorized at the top and bottom 2.5 percentiles.
BankruptAfter	Binary variable equal to one if the firm has filed for bankrupcty within four years after receiving loan financing, and equal to zero otherwise.
InactiveAfter	Binary variable equal to one if the firm is inactive four years after receiving loan financing, and equal to zero otherwise. Inactivity is defined as zero sales and labor costs.
OperatingDeficitAfter	Binary variable equal to one if the firm has had operating deficits in one or more years after receiving loan financing, and equal to zero otherwise.
NewspaperSub.	Average number of newspaper subscriptions per household in the municipality where the firms is located. Excluding tabloid and freely distributed papers.

Table A.10:
Definitions of regression variables.

Variable	Definition
MarketShare (x-y emp.)	Community bank market share for firms with x-y employees measured in terms of number of loans.
ln(Employees)	Natural logarithm of firm employees.
ln(SecurityAssets)	Natural logarithm of assets suitable as collateral security (current assets plus real estate).
ln(Sales)	Natural logarithm of firm sales.
FirmAge (xx-yy)	Binary variable equal to one if firm age is xx-yy years, and equal to zero otherwise.
ln(AltCredit)	Natural logarithm of alternative non-equity finance, this includes the sum of convertible loans, subordinated loan capital, loans to mother company and industry bonds.
OperatingMargin	Operating profits relative to sales.
OwnerAge (xx-yy)	Binary variable equal to one if the majority owner is xx-yy years old, and equal to zero otherwise.
OwnerBankrupcty	Binary variable equal to one if the owner of the firm has been involved in a bankruptcy the past two years, and equal to zero otherwise.
Industry (2-digit NACE)	Binary dummy variable for each of the 2-digit NACE codes.
Industry (A-V)	Binary dummy variable for each of the A-V NACE codes.
Centrality (1-5)	Binary dummy variable for each of the five categories of municipality centrality.
Treated	Binary variable equal to one if the firm receives long term loan from a community bank, and equal to zero otherwise.
After	Binary variable equal to one in the period after the firm has received long term loan financing, and equal to zero otherwise.
ln(Loan)	Natural logarithm of the size of the long term loan the firm received.
ln(Sales l.treat)	Natural logarithm of the firm's sales the year before treatment.
ln (LaborCosts l.treat)	Natural logarithm of the firm's labor costs the year before treatment.
YearTreatment	Binary dummy variable equal to one for the respective year the firm received treatment.
FirmSize	Binary dummy variables for firm size categories (1-10 employees, 11-20 employees and 21-50 employees).
FirmAge	Binary dummy variables for firm age categories (0-5 years, 6-10 years, 11-20 years and more than 20 years)
NewspaperSubscription	Average number of newspaper subscriptions per household in the municipality where the firms is located. Excluding tabloid and freely distributed papers.
Active	Binary variable equal to one if the firm has labor costs or sales, and equal to zero otherwise.
Bankrupt	Binary variable equal to one if the firm has filed for bankruptcy, and equal to zero otherwise.
Deficit	Binary variable equal to one if the firm has operational deficits, and equal to zero otherwise.
ln(Sales+1)	Natural logarithm of sales plus NOK 1 million.
ln(VA+1)	Natural logarithm of value added plus NOK 1 million.
ln(Employees+1)	Natural logarithm of number of employees.
OM	Operating margins
ln(Debt+1)	Natural logarithm of long term debt from credit institutions plus NOK 1 million.

Appendix B

Appendix to Chapter 3

B.1 The low-risk loan program

The screening processes of market based loans, commonly referred to as low risk loans, and the innovation loans are performed by the same institution and the same loan officers. Thus, it adds information to see the results from the effect study of the low risk loan program and the innovation loan program in context. Since the low risk loan program in many respects is run and administrated like a private bank, the performance study of the low risk loans isolates the effect of whether bureaucrats are able to operate regular credit institutions.

What I measure here is the administrative selection competency of the low risk loan program. That is, whether the loan officers at Innovation Norway have the competency to select firms eligible for debt financing. Consequently, when measuring the effect of the innovation loan program on firm survival and growth, I have information about the quality of the administrative competency of the lending institution based on the low risk loan program. The results regarding the innovation loan portfolio can be interpreted in light of this.

Given that the low risk loan program is a scheme not much different from any other bank, I expect that firms receiving low risk loans perform on the same level as firms with private bank financing. If the firms with low risk loans perform on the same level this would suggest that Innovation Norway is successful in their screening.

In the period 2004 to 2009 there were 371 service and industry related projects split on 304 firms which received low risk loans from Innovation Norway. Excluding firms for which the loan financing is smaller than 20% of the firm's assets the year before the loan was paid out the sample is reduced to 218 firms. Of the 218 firms 149 had common support. 62 did not find a match with the caliper set at 0.05, and 7 were excluded due to missing data points.

Table B.1 contains pre-treatment statistics on a matched sample of firms with innovation loans and firms with private bank loans. The table shows that the firms with low risk loans and the control group of firms with private bank loans have similar means. The t-tests do not find statistically significant differences in the two samples. Although not displayed I have also made a graphical comparison of the distribution of the samples with respect to sales, value added, total assets and loan size. All of this points in the direction that the control group is a good match. To the extent that the differences between treated and controls are not removed I control for the same pre-treatment characteristics in the regression on the matched sample.

Table B.1: Comparison of pre-treatment means of matched variables for firms with low risk loans within industry and services and control group of firms with loans from private banks.

	Mean			t-test	
Variable	(1) Treated	(2) Control	(3) *%bias*	(4) t	(5) $p \geq \|t\|$
Sales	9,062	11,053	-8.7	-0.74	0.462
Employees	7.1	6.3	5.7	0.47	0.637
ValueAdded	3,275	4149	-10.2	-0.86	0.392
TotalAssets	13,306	17,970	-11	-0.93	0.355
Loan	6,478	7,355	-5.2	-0.44	0.662
SalesGrowth	.020	.025	-2.4	-0.18	0.857
EmployeeGrowth	-.002	.013	-5.1	-0.38	0.702
FirmAge	9.1	10.1	-10.5	-0.86	0.388

Note: Column 1 displays the mean value of the matched variables at t-1 for the firms with low risk loans. Similarly, Column 2 displays the mean value for the control group at t-1. In the matching I use log transformed variables and the square of the log transformed variables, while the table displays the absolute values. The %bias reported in Column 3 is the percentage difference of the sample means in the treated and non-treated as a percentage of the square root of the average of the sample variances in the treated and non-treated groups (formulae from Rosenbaum and Rubin, 1985). Column 4 and 5 display the t-tests for equality of means in the two samples. The null-hypothesis is that the means are equal and thus a low t-value will not reject this hypothesis.

Table B.2 displays the results from the regression analysis of firms with low risk loans compared to a control group of firms with private bank loans. The *Treated* estimates in Table B.2 tell us that the treated and the control group are not at statistically significant different levels pre-treatment. The only exception is operating returns on assets (OROA), where the return is significantly weaker at the 10% level for the group of firms with low risk loans. A separate regression on the matched sample, not displayed due to brevity, tells us that the matched sample does not have a statistically significant different pre-treatment growth in any of the performance variables. This suggests that the treated and the firms are on the same trend growth, and that the differences-in-differences estimates are not biased.

The *Treated*After* estimate of the active variable, see Column 1, displays no statistically significant differences between the firms with low risk loans and regular private bank loans with respect to becoming inactive in the period after the loan was paid out. There are also no statistically significant differences between the two groups of firms with respect to the probability of running operational deficits, Column 2, after the loan was paid out. These results suggest that there are no differences between the low risk loan portfolio and the private bank loan portfolio with respect to bankruptcy or rates of debt defaults.

The *After* estimates shows a statistically significant positive growth in sales, value added, number of employees and total assets for both the firms with low risk loans and the control group of firms with private credit. The differences between the firms with low risk loans and the firms with private bank loans post-treatment are generally small and insignificant. The exception here is growth in total assets where I find that the firms with low risk loans have a significantly stronger growth in total assets. Asset growth signals an ability to gain resources, either from running profits or from additional loan uptake or equity issues. It is surprising that the firms with low risk loans have a stronger growth in assets without also having either a stronger growth in e.g. sales, or a weaker development in profitability.

TABLE B.2: Survival, growth and profitability of industry and service firms with low risk loans from Innovation Norway compared to firms with private bank loans.

	(1) Active Coef./SE	(2) Deficit Coef./SE	(3) ln(sales+2) Coef./SE	(4) ln(va+2) Coef./SE	(5) ln(employees+1) Coef./SE	(6) ln(assets+2) Coef./SE	(7) OROA Coef./SE
Treated		.026	.014	-.020	-.009	-.002	-.040*
		(.05)	(.05)	(.04)	(.04)	(.03)	(.02)
After		-.067*	.320***	.208***	.134***	.349***	-.018
		(.04)	(.06)	(.04)	(.05)	(.05)	(.02)
Treated*After	-.022	-.010	-.008	.021	.035	.215**	.028
	(.04)	(.05)	(.09)	(.06)	(.08)	(.08)	(.02)
Estimation method	Probit	Probit	OLS	OLS	OLS	OLS	OLS
F-value			129.5	142.5	229.9	91.23	5.143
Adjusted R-squared			.7745	.638	.8105	.7057	.0611
Log-likelihood	-607	-1,112	-1,560	-1,291	-1,473	-1,553	714
Chi-Square	67	117					
No. of obs.	1,476	2,004	1,687	1,676	1,693	1,687	1,687

Clustered standard errors (SE) at the firm level are reported in parentheses: * significance at ten, ** five, *** one percent.

Note: This table displays pre- and post-treatment differences between firms with low risk loans from Innovation Norway and a control group of firms with private credit. The sample is constructed by using propensity score matching and contains firms receiving long term credit financing during the time period 2004-2009. The data is a panel covering a window of two years before and until seven years after treatment. See Table 3.2 for a more detailed description of the table.

B.2 Variable definitions and robustness results

TABLE B.3:
Definitions of regression variables.

Variable	Definition
Sales	Firm sales (1000 NOK).
Employees	Number of employees registered with the firm.
TotalAssets	The firm's total assets (1000 NOK).
ValueAdded	The firm's gross value added (sum of operating results, labor costs, write offs and write downs) (1000 NOK).
YearTreatment	Binary dummy variable equal to one for the respective year the firm received treatment.
FirmAge	Number of years since the firm was established at the time of treatment.
Loan	The change in long term loan financing at the time of treatment (1000 NOK).
InnovationLoan	The firm's amount of long term loan financing from a credit institution (1000 NOK).
SalesGrowth	Difference in ln(sales+2) from year t-2 to t-1. Winzorized at the top and bottom 2.5 percentiles.
EmployeeGrowth	Difference in ln(employees+2) from year t-2 to t-1. Winzorized at the top and bottom 2.5 percentiles.
Treated	Binary variable equal to one if the firm receives an innovation loan, and equal to zero otherwise.
After	Binary variable equal to one in the period after the firm has received an innovation loan, and equal to zero otherwise.
Active	Binary variable equal to one if the firm has labor costs or sales, and equal to zero otherwise.
Deficit	Binary variable equal to one if the firm has operational deficits, and equal to zero otherwise.
ln(sales+2)	Natural logarithm of sales plus NOK 2 million.
ln(va+2)	Natural logarithm of value added plus NOK 2 million.
ln(employees+1)	Natural logarithm of number of employees plus 1.
ln(assets+1)	Natural logarithm of total assets plus NOK 2 million.
OROA	The firm's operating results on assets. Winzorized at the top and bottom 2.5 percentiles.

TABLE B.4: Survival, growth and profitability of firms which were granted innovation loans compared to firms that were rejected by the program (detailed estimates on performance pre- and post-treatment).

	(1) Active Coef./SE	(2) Deficit Coef./SE	(3) ln(sales+2) Coef./SE	(4) log(va+2) Coef./SE	(5) ln(employees+1) Coef./SE	(6) ln(assets+2) Coef./SE	(7) OROA Coef./SE
2 years before treatment		-.054	-.025	-.029	-.037	.045	.010
		(.10)	(.09)	(.10)	(.12)	(.09)	(.07)
(1-2) years after treatment		.133	-.119	-.183	-.131	-.001	-.044
		(.13)	(.10)	(.14)	(.10)	(.10)	(.06)
(3-4) years after treatment		-.055	-.104	-.066	-.302**	-.019	.082
		(.10)	(.12)	(.13)	(.12)	(.15)	(.09)
(5-8) years after treatment		-.265**	-.004	.075	-.413*	-.229	.351***
		(.13)	(.15)	(.17)	(.21)	(.18)	(.11)
Treated*2 years before treatment		.004	-.057	-.237	-.039	-.156*	.089
		(.12)	(.12)	(.16)	(.13)	(.09)	(.09)
Treated*1 year before treatment		.081	-.025	-.201	.035	.010	.025
		(.13)	(.07)	(.14)	(.07)	(.06)	(.08)
Treated*(1-2) years after treatment	.060	-.129	.257**	.235	.317**	.273**	.125*
	(.04)	(.13)	(.12)	(.17)	(.12)	(.14)	(.06)
Treated*(3-4) years after treatment	-.070	.043	.181	.099	.403***	.378**	.039
	(.06)	(.11)	(.13)	(.17)	(.15)	(.18)	(.08)
Treated*(5-8) years after treatment	-.215**	.167	.376*	.089	.631**	.705***	-.190**
	(.10)	(.11)	(.19)	(.19)	(.25)	(.24)	(.09)
Estimation method	Probit	Probit	OLS	OLS	OLS	OLS	OLS
F-value			70.49	25.04	73.89	62.58	5.239
Adjusted R-squared			.7807	.5483	.7425	.7104	.1199
Log-likelihood	-185	-483	-657	-803	-733	-761	-205
Chi-Square	90	66					
No. of obs.	632	807	807	737	808	807	789

Clustered standard errors (SE) at the firm level are reported in parentheses: * significance at ten, ** five, *** one percent.
Note: The regression is run on the same sample with the same control variables as the regressions displayed in Table 3.2. The only difference is that this regression includes detailed estimates on pre- and post-differences between firms that were granted innovation loans from Innovation Norway and those rejected. The *X years before/after treatment* estimates are the common level differences for both groups compared to the reference year t-1. The interacted dummy variables *Treated*X years before/after treatment* should be interpreted as the innovation loan firms' deviation from the common level at each point in time. The regression in Column 1, *Active*, only estimates post-treatment differences.

TABLE B.5: Survival, growth and profitability of firms with innovation loans compared to firms with private bank loans: Firm performance over time.

	(1) Active Coef./SE	(2) Deficit Coef./SE	(3) ln(sales+2) Coef./SE	(4) log(va+2) Coef./SE	(5) ln(employees+1) Coef./SE	(6) ln(assets+2) Coef./SE	(7) OROA Coef./SE
2 years before treatment)		-.035	-.061*	-.019	-.027	-.127***	-.014
		(.05)	(.04)	(.04)	(.06)	(.03)	(.03)
(1-2) years after treatment		.049	.072	.085	.052	.157***	-.055*
		(.07)	(.05)	(.06)	(.06)	(.05)	(.03)
(3-4) years after treatment		.098	.101	.092	.081	.183***	-.070**
		(.07)	(.06)	(.06)	(.07)	(.06)	(.03)
(5-8) years after treatment		-.030	.135	.118	.134	.077	-.077*
		(.09)	(.14)	(.12)	(.13)	(.11)	(.04)
Treated*2 years before treatment		.279***	.006	-.255**	-.037	-.017	-.245***
		(.07)	(.06)	(.10)	(.07)	(.05)	(.05)
Treated*1 year before treatment		.319***	.025	-.156**	.036	-.004	-.287***
		(.06)	(.03)	(.08)	(.03)	(.03)	(.04)
Treated*(1-2) years after treatment	.039	.215***	.090	.025	.135**	.133*	-.169***
	(.03)	(.07)	(.07)	(.07)	(.07)	(.07)	(.04)
Treated*(3-4) years after treatment	-.086*	.093	.023	-.013	-.043	.170	-.100**
	(.05)	(.08)	(.09)	(.09)	(.11)	(.11)	(.04)
Treated*(5-8) years after treatment	-.258***	.207*	.427**	.158	.115	.481*	-.062
	(.09)	(.11)	(.21)	(.18)	(.25)	(.25)	(.06)
Estimation method	Probit	Probit	OLS	OLS	OLS	OLS	OLS
F-value			77.77	30.29	102.9	97.52	4.826
Adjusted R-squared			.7431	.5178	.7555	.7506	.1249
Log-likelihood	-282	-723	-938	-1,017	-985	-970	-168
Chi-Square	58	74					
No. of obs.	932	1,201	1,167	1,116	1,172	1,167	1,145

Clustered standard errors (SE) at the firm level are reported in parentheses: * significance at ten, ** five, *** one percent.

Note: The table depicts detailed estimates on pre- and post-differences between firms with innovation loans from Innovation Norway and firms with private bank loans. The *Treated*Before/Treated*After* should be interpreted as the innovation loan firms' deviation from trend at each point in time. For example, the *Treated*Before (t-2)* estimate is the estimated difference for the innovation loan firms from the *Before (t-2)* estimate. The regression is run on the same sample with the same control variables as the regressions displayed in Table 3.4. The year before treatment, $t-1$, is the reference year for the *before/after* estimates.

TABLE B.6: Survival, growth and profitability of firms with innovation loans compared to firms with venture capital financing: Firm performance over time.

	(1) Active Coef./SE	(2) Deficit Coef./SE	(3) ln(sales+2) Coef./SE	(4) log(va+2) Coef./SE	(5) ln(employees+1) Coef./SE	(6) ln(assets+2) Coef./SE	(7) OROA Coef./SE
2 years before treatment		-.127	-.144*	.112	-.166*	-.108**	.080*
		(.11)	(.07)	(.13)	(.09)	(.05)	(.04)
(1-2) years after treatment		.230**	.176**	.087	.302***	.398***	-.124***
		(.09)	(.08)	(.17)	(.08)	(.09)	(.04)
(3-4) years after treatment		.145	.190	.351*	.330***	.451***	-.069
		(.11)	(.13)	(.20)	(.11)	(.14)	(.06)
(5-8) years after treatment		.257**	.564***	.468*	.353	.721***	-.123
		(.13)	(.17)	(.28)	(.26)	(.19)	(.09)
Treated*2 years before treatment		.072	.110	-.127	-.017	-.010	-.072
		(.11)	(.09)	(.12)	(.09)	(.06)	(.06)
Treated*1 year before treatment		.041	.049*	.078	-.006	.020	-.027
		(.09)	(.03)	(.15)	(.04)	(.04)	(.05)
Treated*(1-2) years after treatment	.020	-.252***	.009	.235	-.179*	-.134	.162***
	(.04)	(.09)	(.09)	(.17)	(.10)	(.11)	(.05)
Treated*(3-4) years after treatment	-.121*	-.235**	-.008	-.021	-.305**	-.216	.158***
	(.06)	(.10)	(.14)	(.17)	(.14)	(.15)	(.06)
Treated*(5-8) years after treatment	-.252**	-.345***	-.077	.003	-.267	-.407*	.247**
	(.11)	(.12)	(.22)	(.33)	(.32)	(.23)	(.10)
Estimation method	Probit	Probit	OLS	OLS	OLS	OLS	OLS
F-value			168.4	29.37	96.44	113	5.6
Adjusted R-squared			.8139	.5502	.7619	.7637	.1511
Log-likelihood	-228	-538	-730	-980	-830	-766	-196
Chi-Square	63	84					
No. of obs.	729	931	931	861	933	931	907

Clustered standard errors (SE) at the firm level are reported in parentheses: * significance at ten, ** five, *** one percent.
Note: The regression is run on the same sample with the same control variables as the regressions displayed in Table 3.7. The year before treatment, $t-1$, is the reference year for the *X years before/after treatment* estimates. See Table B.4 for more on the interpretation of the estimated coefficients.

Appendix C

Appendix to Chapter 4

C.1 Descriptive statistics and robustness tests

Table C.1:
Sample summary statistics.

	Mean	**Stdev.**	**p25**	**p50**	**p75**	**N**
Sales	13,403	40,093	2,729	5,438	12,455	166,137
Investments	423	5,798	0	34	221	166,137
Employees	10.0	22.9	3.0	5.0	11.0	163,100
LaborCost	2,833	7,680	884	1,447	2,717	166,137
ValuedAdded	3,830	11,135	1,121	1,944	3,681	166,137
Equity (book value)	3,126	83,753	163	478	1,298	166,137
TotalAssets (book value)	9,398	150,321	1,252	2,579	5,525	166,137
InvestmentRatio	0.043	0.550	0.000	0.013	0.064	166,020
FirmAge	12.4	11.1	5.0	10.0	17.0	166,137
OwnerAge	49.4	10.0	42.0	49.0	57.0	166,137
CEOAge	47.8	9.8	40.0	48.0	55.0	126,250
OwnerCEO	0.68		0.00	1.00	1.00	126,248
OwnershipTransfer	0.06		0.00	0.00	0.00	166,137
CEOChange	0.05		0.00	0.00	0.00	166,137

Note: This table contains statistics for the dependent and independent variables in the regression analysis. The statistics is for the entire sample period 2000 to 2009. All nominal amounts are in 1,000 1999-NOK. Information on the firm CEO is missing from the sample for the year 2006.

Table C.2:
Distribution of owners by age cohorts.

Age cohort	Number of observations	Share of total sample (percent)
≤ 50	89,247	53.7
$51 - 55$	29,492	17.8
$56 - 60$	25,024	15.1
$61 - 65$	14,438	8.7
$66 - 70$	5,044	3.0
$71 - 75$	1,711	1.0
> 75	1,181	0.7
Total	166,137	100.0

Note: The table present the age distribution of majority owners based on the panel data set for the years 2000 to 2009.

Table C.3:
Distribution of CEOs by age cohorts.

Age cohort	Number of observations	Share of total sample (percent)
≤ 50	74,922	59.3
$51 - 55$	21,510	17.0
$56 - 60$	17,031	13.5
$61 - 65$	9,129	7.2
$66 - 70$	2,618	2.1
$71 - 75$	738	0.6
> 75	302	0.2
Total	126,250	100.0

Note: The table presents the age distribution of CEOs on the panel data set for the years 2000 to 2009 except the year 2006.

FIGURE C.1: Distribution of owners by firm owner age.
The graph shows the age distribution of owners in the years 2000 and 2009, respectively.

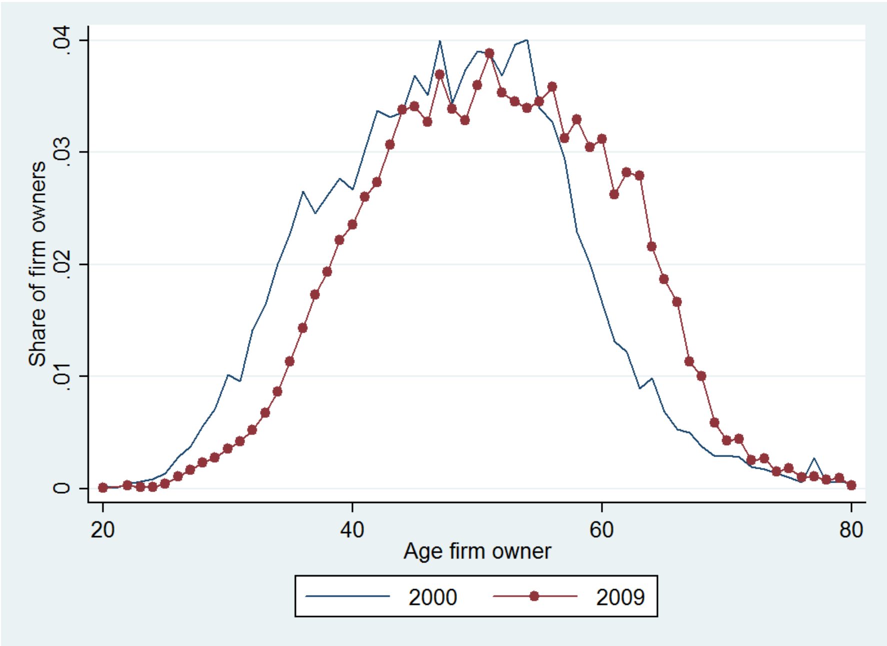

FIGURE C.2: Share of firms with investment spike by age (2000–2009).
The vertical axis measures the share of firms with an investment spike, where an investment spike is measured as in Equation 4.2.

TABLE C.4: Log odds ratio of investment spikes.

Investment ratio	$max[\alpha\mu(K_{i,t-1}), 0.10]$			$max[\alpha\mu(K_{i,t-1}), 0.20]$			$max[\alpha\mu(K_{i,t-1}), 0.30]$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE	Coef./SE
OwnerAge51to55	-.061	-.152**	-.152**	-.036	-.101	-.100	-.046	-.161**	-.160**
	(.04)	(.07)	(.07)	(.04)	(.07)	(.07)	(.04)	(.07)	(.07)
OwnerAge56to60	-.095*	-.194**	-.202**	-.043	-.074	-.105	-.011	-.057	-.064
	(.05)	(.08)	(.08)	(.06)	(.08)	(.09)	(.06)	(.09)	(.09)
OwnerAge61to65	-.185***	-.314***	-.319***	-.103	-.175*	-.202**	-.059	-.157	-.163
	(.07)	(.09)	(.10)	(.07)	(.10)	(.10)	(.08)	(.11)	(.11)
OwnerAge66to70	-.205**	-.114	-.119	-.191*	-.182	-.206	-.110	-.182	-.187
	(.09)	(.12)	(.12)	(.10)	(.13)	(.13)	(.11)	(.14)	(.14)
OwnerAge70to75	-.391***	-.328*	-.331*	-.346**	-.445**	-.466**	-.331*	-.448**	-.455**
	(.15)	(.18)	(.18)	(.16)	(.19)	(.19)	(.17)	(.20)	(.20)
OwnerAge> 75	-.202	.066	.064	-.327	-.138	-.144	-.519**	-.373	-.365
	(.21)	(.24)	(.24)	(.23)	(.25)	(.26)	(.25)	(.28)	(.29)
CEOAge51to55		.048	.047		.038	.038		.092	.092
		(.06)	(.06)		(.07)	(.07)		(.07)	(.07)
CEOAge56to60		.004	-.010		-.051	-.110		-.028	-.041
		(.07)	(.08)		(.08)	(.09)		(.08)	(.09)
CEOAge61to65		.084	.069		.017	-.049		.048	.034
		(.09)	(.10)		(.09)	(.10)		(.10)	(.11)
CEOAge66to70		-.300**	-.315**		-.116	-.182		-.005	-.019
		(.13)	(.14)		(.14)	(.14)		(.14)	(.15)
CEOAge71to75		-.385*	-.399*		-.039	-.097		-.056	-.067
		(.23)	(.23)		(.24)	(.24)		(.26)	(.26)
CEOAge> 75		-1.059***	-1.068***		-.727*	-.770*		-1.054**	-1.069**
		(.37)	(.37)		(.39)	(.39)		(.48)	(.48)
Owner-CEOAge> 55			.026			.114			.025
			(.07)			(.07)			(.08)
Log-likelihood	-25,433	-18,028	-18,028	-23,538	-16,621	-16,619	-21,550	-15,178	-15,176
Chi-Square	369	303	304	364	286	289	353	274	274
No. of obs.	68,935	48,640	48,639	66,613	46,379	46,377	63,528	43,811	43,806

Note: The table reports log-odds ratios of having an investment spike. The estimates are based on a fixed effect logit model. The data set covers the period 2000 to 2009. The independent variables are the same as described in Equation 4.1. Standard errors are reported in parentheses: * significance at ten, ** five, *** one percent.

Table C.5: Effects on value added of owner and CEO age

Employees	(1) ≥ 2 Coef./SE	(2) ≥ 4 Coef./SE	(3) ≥ 8 Coef./SE	(4) ≥ 10 Coef./SE	(5) ≥ 20 Coef./SE	(6) < 20 Coef./SE
OwnerAge51to55	-.001	.005	-.010	-.014	-.048	.005
	(.02)	(.02)	(.03)	(.03)	(.04)	(.03)
OwnerAge56to60	-.022	.007	-.028	-.068**	-.050	-.028
	(.03)	(.03)	(.03)	(.03)	(.05)	(.03)
OwnerAge61to65	.014	.025	-.002	-.025	-.052	.023
	(.03)	(.03)	(.04)	(.04)	(.06)	(.04)
OwnerAge66to70	.014	-.001	-.043	-.078	-.045	.011
	(.04)	(.04)	(.05)	(.05)	(.08)	(.05)
OwnerAge71to75	-.066	-.030	-.080	-.035	-.216*	-.066
	(.06)	(.06)	(.07)	(.07)	(.11)	(.07)
OwnerAge>75	.011	-.051	-.069	.196*	-.194	.035
	(.08)	(.08)	(.09)	(.11)	(.16)	(.09)
CEOAge51to55	-.018	-.024	-.033	-.038	-.023	-.016
	(.02)	(.02)	(.02)	(.03)	(.04)	(.03)
CEOAge56to60	.014	-.015	-.011	.018	.007	.025
	(.03)	(.03)	(.03)	(.03)	(.05)	(.03)
CEOAge61to65	-.051*	-.068**	-.071**	-.051	-.005	-.061*
	(.03)	(.03)	(.04)	(.04)	(.06)	(.04)
CEOAge66to70	-.163***	-.159***	-.160***	-.113**	-.140	-.163***
	(.04)	(.04)	(.05)	(.06)	(.09)	(.05)
CEOAge71to75	-.086	-.141**	-.142*	.011	.067	-.092
	(.07)	(.07)	(.08)	(.09)	(.16)	(.08)
CEOAge>75	-.525***	-.482***	-.524***	-.338**	-.039	-.558***
	(.11)	(.11)	(.13)	(.15)	(.30)	(.12)
Owner-CEOAge>55	-.020	-.015	-.019	-.028	-.033	-.018
	(.02)	(.02)	(.02)	(.03)	(.04)	(.02)
OwnershipTransfer	.072***	.032	.000	-.009	-.044	.079***
	(.03)	(.03)	(.03)	(.03)	(.05)	(.03)
CEOChange	.016	.033	.053**	.038	-.016	.020
	(.02)	(.02)	(.02)	(.02)	(.04)	(.03)
ln(l.Investment)	YES	YES	YES	YES	YES	YES
ln(l2.Investment)	YES	YES	YES	YES	YES	YES
ln(Employees+1)	YES	YES	YES	YES	YES	YES
FirmAge(d)	YES	YES	YES	YES	YES	YES
Year(d)*Industry(d)	YES	YES	YES	YES	YES	YES
F-value	32.75	33.02	26.28	23.21	13.22	23.98
R-squared	.1875	.2092	.2503	.2739	.3466	.1693
No. of obs.	85,396	74,671	47,256	36,621	14,491	70,905

Note: This table reports the estimated effects on log-value added on a panel data set covering the years 2000 to 2009. The independent variables are the same as described in Equation 4.1, except that I control for two periods of lagged log-investments and log-employment. Moving from left to right in the table the minimum level of firm employees during the sample period increases. See Table C.7 for variable definitions. Standard errors are reported in parentheses: * significance at ten, ** five, *** one percent.

Table C.6: Aggregate productivity effect for Norway of aging CEOs.

	Firm average				Total	
	(1)	(2)	(3)	(4)	(5)	(6)
Age	**Estimate**	**Value added**	**Counterfactual**	**Loss**	**No. firms**	**Loss**
$51-55$	0.000	5.1	5.1	0.0	7,473	0
$56-60$	0.000	5.0	5.0	0.0	5,917	0
$61-65$	0.000	5.0	5.0	0.0	3,844	0
$66-70$	-0.163	4.7	5.6	-0.9	1,491	-1,355
$71-75$	0.000	4.9	4.9	0.0	309	0
> 75	-0.558	3.3	7.4	-4.1	95	-393
Total					45,803	-1,748

Note: The estimates in Column 1 can be interpreted as percentage points. Nominal amounts are in million Norwegian 2013-kroner. The average counterfactual value added per firm is calculated by dividing the factual value added figure, Column 2, by one plus the age cohort point estimate, Column 1. The total productivity loss, Column 6, is calculated by multiplying the average firm productivity loss, Column 4, with the total number of firms per CEO age cohort, Column 5.

Table C.7:
Definitions of regression variables.

Variable	Definition
Sales	Firm sales (1,000 NOK).
Investments	Firm real investments (1,000 NOK). Calculated as the year by year difference in non-financial fixed assets plus write-offs and write-downs of non-financial assets.
Employees	Number of employees registered with the firm.
LaborCost	Firm labor costs (1,000 NOK). Includes wages, bonuses and commissions as well as taxes.
ValueAdded	The firm's gross value added (sum of operating results, laborcosts, write offs and write downs) (1000 NOK).
Equity (book value)	Book value of firm equity (1,000 NOK).
TotalAssets (book value)	Book value of firm total assets (1000 NOK).
InvestmentRatio	Real investments divided by total assets.
FirmAge	Number of years since the firm was established.
OwnerAge	The age of the majority owner of the firm.
OwnerCEO	Binary variable equal to one if the firm's majority owner and CEO is the same person, and equal to zero otherwise.
OwnerAgeXtoY	Binary variable equal to one if the firm's majority owner is in the age span X-Y, and equal to zero otherwise.
CEOAgeXtoY	Binary variable equal to one if the firm's CEO is in the age span X-Y, and equal to zero otherwise.
Owner-CEOAge$>$ 55	Binary variable equal to one if the firm's owner is older than 55 years and holds position as CEO, and equal to zero otherwise.
OwnershipTransfer	Binary variable equal to one if the firm's majority owner has changed, and equal to zero otherwise.
CEOChange	Binary variable equal to one if the CEO owner has changed, and equal to zero otherwise.
ln(l.Investment)	Natural logarithm of real investments lagged one period.
ln(Employees+1)	Natural logarithm of number of employees plus 1.
FirmAge(d)	Firm age dummies. 5-year cohorts from zero to 50 years.
Year(d)	Year dummies.
Year(d)*Industry(d)	Year-industry (2-digit NACE) dummies.