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Does Innovation Norway's grants have an effect?

An empirical research paper examining the effects of the establishing grant and development grants

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Abstract

This paper examines the possible effects of government financial support to firms through Innovation Norway (IN). We compare firms that received support from IN in the years 2006-2010 with comparable firms that applied for support, but were rejected. To manage potential endogeneity problems, we assess the effects of IN support by combining propensity score matching with a differences-in-differences estimation. We thereby control for observable firm characteristics and fixed firm effects. The treatment effects of participation are estimated for two types of IN grants: Establishing grants and development grants. The treatment effects are measured as differences in growth between the treated and matched firms the first two and three years after receiving IN support.

We find no evidence that establishing grants have positive effects on value creation, number of employees or return on assets. We even find some evidence of negative effects of receiving establishing grants on operating profits and sales revenue. However, the results for sales revenue are not robust, and the results for operating profits are only significant two years after treatment. For development grants, we find significant positive effects on operating profits and employment. On the other hand, we find no clear evidence that development grants have positive effects on value creation, sales revenue or return on assets.

Preface

This master thesis represents the conclusion of our studies at the Norwegian School of Economics.

Firstly, we would like to thank our supervisor Carsten Bienz for giving us honest feedback and advice. We thank Per Arve Frøyen, Christopher Rosenkilde and Marianne Von Krogh at Innovation Norway for providing us with useful insights on Innovation Norway's priorities and on the selection process for grants. We also thank Chunbo Liu for his input on econometric issues.

For providing us with access to data, we would like to thank Diana Medel Carrero at Innovation Norway, Sigmund Tveit at NSD and Kellis Akselsen at SNF. Finally, we thank friends and family for their comments and input.

Bergen, June 15, 2016

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Introduction

Is the Norwegian government's funding of businesses an effective use of taxpayers' money in terms of growth and value creation in the Norwegian economy? In this empirical study, we compare the growth and performance of Innovation Norway (IN) supported businesses, hereby named treatment group or treated firms, with comparable businesses. We have focused on the establishing grant and development grants, and we discuss whether IN could reallocate funds in order to create more value. In order to do so, we apply propensity score matching with differences-in-differences (DD) estimation to investigate the possible effects on growth, employment and profitability of grants from Innovation Norway. The awardees of grants are matched to a control group of firms, hereby referred to as untreated firms, based on the observable characteristics industry, size, application year and geographic location. The untreated firms are firms that applied for grants, but were rejected. The DD estimator also allows for unobservable time-invariant differences in outcomes between treated and untreated firms. We measure the effects of IN support 2-3 years after assignment to treatment.

Based on the analysis there is no evidence that receiving establishing grants have positive effects on growth and profitability. There is even some evidence of negative effects on operating profits and sales revenue from receiving establishing grants. However, the results are not robust to outliers or to the choice of matching method. We find that receiving development grants has positive effects on growth in operating profits and employment. Firms receiving development grants grew by 9-10 more employees than comparable firms that did not receive grants. The mean compound annual growth rate for employment for the treated firms was 13.13 percent and 0.22 percent for the untreated firms. The results for employment are highly significant, and robust to outliers and choice of matching method. The operating profits for treated firms have grown by around 2.5 million more relative to untreated firms. The results are highly significant, and robust to the choice of matching method and treatment of outliers. In terms of mean compound annual growth rates, the operating profits of treated firms have grown by 46.62 percent, while the untreated firms have had a negative annual growth of 5.92 percent. Nevertheless, the results seem to be influenced by within-firm correlation for the firms receiving several treatment, and are no longer significant when clustering the standard errors. We find no clear evidence that development grants have positive effect on value creation, sales revenue and return on assets.

There are several reasons why a greater comprehension of the Norwegian government's involvement the capital markets has become more imperative. Norway has experienced significant economic shocks in recent time. A declining oil price and a depreciated Norwegian Krone has caused the Norwegian government to invest more money and time into restructuring the economy. In October 2015, the Ministry of Trade and Industry Affairs presented a plan to make Norway a country for entrepreneurs (The Government of Norway, 2015). Some of the measures taken in order to achieve this was to ease the access to capital, competence and networks for Norwegian companies. As the Minister of Trade and Industry Affairs stated, "We need to facilitate new employment in both the short and long term. For that reason, more good entrepreneurs launching new profitable businesses are needed." Entrepreneurship and innovation are important factors in the development of national economic growth. As a result of a more globalized world, environmental issues and a more competitive business environment, the focus and relevance of entrepreneurship and innovation has increased in recent time. These changes require a greater ability from the Norwegian economy to adapt, and the capability to do so will be crucial in the current as well as potential future economic downturn.

Small business growth will play an important part of this adaption, and has been the topic of a considerable part of research papers and academia in recent years. This is largely due to its contribution to job creation and economic growth. Consequently, there has been a growing amount of research evidence demonstrating a positive relationship between entrepreneurship and economic growth (Levie & Autio, 2008; Acs, 2006). A great deal of literature has also conducted studies looking at the effects of entrepreneurship, innovation and government involvement in capital markets. A significant part of the literature confirms the importance of entrepreneurship and innovation, however, there is less agreement regarding the importance and effect of governmental intervention in the capital markets. Furthermore, academic research about the governmental programs is scarce, and the quality of the research varies (Fehder & Hochberg, 2014). The lack of academic consensus, along with an increased spending on government grants to entrepreneurs, has ignited our interest to study the effects of government intervention in the capital markets. We want to enhance the current research, by looking at the effect the Norwegian government's distribution of capital has on growth in Norwegian businesses. Through our contribution, we therefore seek to provide a deeper understanding of Innovation Norway's financial support, in addition to an assessment of how well they perform according to their objectives.

In order to build innovative startups with growth ambitions, capital is necessary throughout the business life cycle. The beginning stages of the life cycle are the most challenging and the most demanding in terms of attaining capital. Consequently, government involvement in these stages is present in several countries all over the world. Innovation Norway serves as the main distributor of state subsidies to entrepreneurship and innovation in Norway. In recent years, there has been an increase in capital allocated to spark growth in the Norwegian economy through Innovation Norway. In the National Budget of 2016, the Government assigned 340 million NOK to Innovation Norway's establishing grant, as opposed to 50 million NOK in 2010 (Innovation Norway, 2016a).

Previous research performed by Statistics Norway (SSB) and Oxford Research has studied the treatment effects on growth and profitability for firms that received support from Innovation Norway in the period 2003-2010. The research investigated to what extent differences in performance could be attributed causally to the support from IN by comparing growth and profitability of treated firms with untreated firms from the general population of firms. Oxford Research investigated the parameters survival rate, bankruptcy, turnover, and economic development in terms of operating profit, value creation and employment to compare the treated and untreated firms. The research found that companies that had received support showed better survival rates, fewer bankruptcies and larger growth rates than the untreated firms. However, for value creation, turnover and operating profits, no significant effect of IN support was detected. The research methodology applied by Oxford Research was criticized in academia, and as a result, SSB received a mandate from IN in 2013 to develop a tool for estimation of public benefit effects from IN support. This report used a new methodology to look at economic development for treated and untreated firms. The results showed that the treated firms in the study had a higher growth in employees relative to the untreated firms, but also that they were less productive and less profitable than the untreated firms (SSB, 2015a).

The research by SSB used propensity score matching (PSM) in combination with a differences-in-differences (DD) estimation to establish a causal relationship between treatment and firm performance. The previous research uses a control group from the general population of firms based on observable firm characteristics. Using PSM to match on observable characteristics together with a DD estimator has also been applied in other research (Bandick & Karpaty, 2007; Marcus, 2012). We build on SSB's research, but use a control sample of companies that applied for treatment and were rejected. This new approach can provide new insights as to whether IN selects the right companies for treatment. Comparing the treated firms with a control sample that applied for support, but were rejected, could make the analysis more solid for inferring causality, than a study using companies from the general population of firms. We base this belief on an endogeneity problem with correlation between a firm's potential for growth, and application and selection for treatment. Firms that apply for IN support are likely to have bigger potential for growth than similar firms that do not apply. By using firms that applied for IN support without receiving it as our control group, we could thereby add validity to our establishment of causality compared to the previous studies.

Innovation Norway

Innovation Norway distributed 2.8 billion NOK in support to value creating business development in Norway in 2014. If you include loans, the number adds up to 6.1 billion NOK (Innovation Norway, 2015). IN provides a broad variety of financial and non-financial services to Norwegian companies, including loans, grants, advisory and help with internationalization.

Innovation Norway administers funds from several awarding authorities; among these are four different ministries, in addition to county governors from the various counties of Norway. The ministries include The Ministry of Fisheries and Industry, The Ministry of Local Government and Regional Development, The Ministry of Agriculture and Food and The Ministry of Foreign Affairs. This imposes a vast range of intentions for the use of the funds. Funds awarded for a given purpose, can be linked directly to items on the budgets of their awarding authorities. Innovation Norway claims that having many missions within the same house provides synergies for their clients and for the Norwegian economy, but it could also produce conflicts of governance. The main goal of the organization is to trigger commercial and socio-economically successful business development, as well as enhancing the economic development in certain regions. In addition, IN wants to assist the development of long-term and sustainable value creation in Norway. Apart from IN's main goal, they also seek to fulfill their secondary objectives. The secondary objectives are to develop more good entrepreneurs, create expansive businesses and to strengthen and facilitate more innovative business environments (Innovation Norway, 2016b). They aspire to do so by assisting viable startups **Invalid source specified.**. In this thesis, we will base our assessment of the effect of IN support on IN's own objectives.

Innovation Norway's Financial Services

IN offers financial services such as loans, grants, guarantees or a combination of these. The loans offered by IN can be divided into two groups, low-risk loans and innovation loans. IN is a long-term flexible lender and collaborator, that contributes through financing innovative growth businesses and businesses with ambitions to grow internationally (Innovation Norway, 2016c). Low-risk loans are offered to companies that need financing due to a long-term capital need. These loans are given under competitive market conditions with a long repayment period and terms adjusted to the companies' needs. Innovation loans, also known as risk loans, are offered by IN to finance companies with profitable projects that are difficult to finance in private credit markets. Figure 1 below displays various sources of IN financing and commercial financing, and where these are suitable depending on the stage of the business.

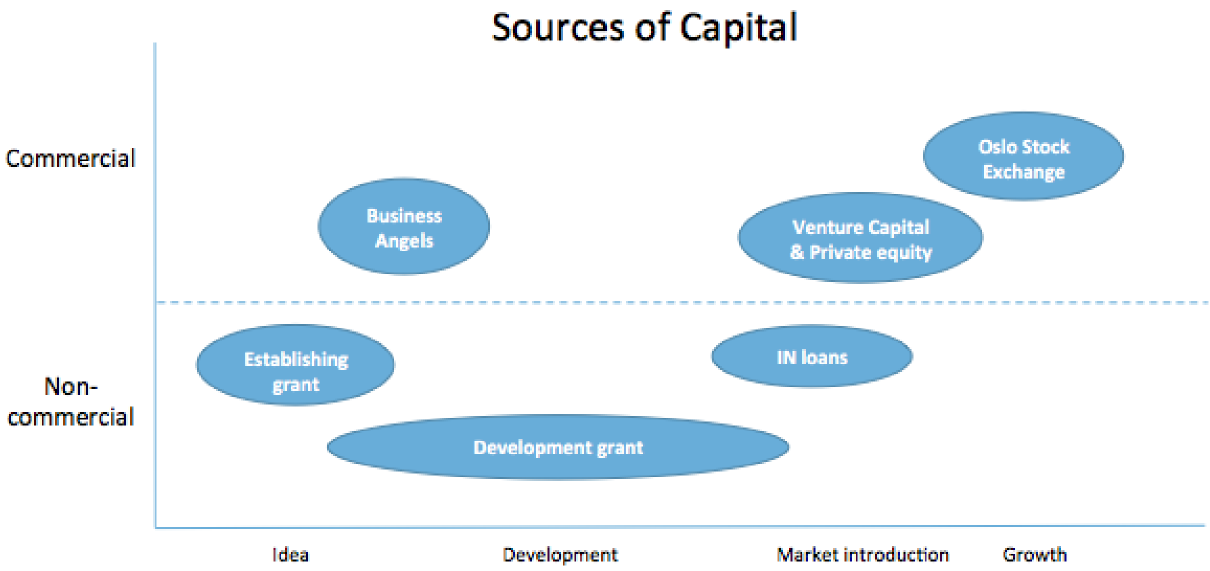

Figure 1: Overview of where the various sources of IN support are suitable, depending on the stage of the business (Innovation Norway, 2016h).

Grants can be applied for different purposes in contributing to the completion of projects that otherwise would not be realized. Public support through grants could entail distorted competition, and is therefore not awarded to businesses where IN assess the risk and consequences of distorted competition to be significant. Grants are given primarily to SMEs all over Norway, however, rural areas receive a relatively higher level of support in comparison to urban areas. The maximum amount one can receive depends on several different factors such as the objective, capital need, company size and location. However, for most businesses the amount usually resides between 10-40 percent of the project's capital need (Innovation Norway, 2016c).

IN uses three measurements to evaluate whether or not a business is eligible for support: The ability to successfully implement the idea or solution, the level of innovation and the potential for value creation (Frøyen & Rosenkilde, 2016). The ability to successfully implement the idea is according to IN the most challenging to measure. This is due to the many intangible qualities that need to be assessed, such as the capabilities of the people working in the business, the relationships and network of the founder/company and commercial viability. The level of innovation is also important, since IN seeks to support innovative ideas. Lastly, potential value creation is evaluated, as enhancing value creation is one of IN's main purposes.

Establishing Grant

The establishing grant is an offer provided by IN to startups with growth ambitions and with a business idea that is innovative and that represents novelty in the market. Between 2010 and 2016, the amount allocated to this grant increased seven-fold. The intention behind the grant is to assist in the beginning phases of starting a company. In the beginning phases for startups, it is important to initiate work with the market and to test the business idea through receiving specific feedback from potential clients. IN offers two levels of establishing grants. The phase in which the startups find themselves will determine the type of support they are eligible for. Companies are not able to apply for both at the same time. Furthermore, IN awards the establishing grant to businesses where it will have a triggering effect. In other words, where the business might have difficulties financing the idea using equity or other means (Frøyen & Rosenkilde, 2016). The grant only covers future expenses, and cannot be used to compensate for sunk costs. In our analysis, we do not differentiate between the two phases of the establishing grant.

Selection Criteria

To qualify for the first phase of support (phase 1), the company needs to have a business idea and to be able to clarify the feasibility of this idea. During this phase, the development of the business is primarily linked to the actual idea. Activities financed by IN grants during this phase could include market research, testing and development of the idea or product, as well as costs due to networking and increasing competence in business development. Grants in this phase range between 50 000 to 100 000 NOK depending on the complexity of the business idea. The scope of the external costs will also affect the financial support. If the project only consists of approved external costs, IN could finance it by up to 100 percent. Less external costs will decrease the amount of IN financing (Innovation Norway, 2016d).

In order to be eligible for the second phase of support (phase 2), the feasibility of the business idea has to be proven through market research. Companies also need to consider whether the business model is rightly adjusted for the market they are entering, and to have conducted commercializing activities. These activities include product and service development, cooperation with potential clients, protection of intangible assets, development of brand strategy or other marketing activities that secure a comprehensive market introduction. The maximum amount of phase 1 and 2 funding is NOK 100,000 and NOK 500,000 respectively. In the second phase, the equity financing requirements are higher than they were in the first phase. It is also not possible to receive more than 600 000 NOK per company, combining both phases (Innovation Norway, 2016d).

Development Grants

IN also awards grants to established companies with projects they consider profitable or that will expand the current business. The projects that receive support should increase value creation and employment in the company. IN allocates development grants on both a regional and a nationwide basis. The regional grants are allocated to business development projects (soft investments) or to some degree the co-financing of physical investments in rural areas. The intention behind these grants is to boost projects promoting innovation and restructuring. The Ministry of Local Government and Modernization funds the regional grants.

The Ministry of Trade, Industry and Fisheries funds development grants that are awarded on a nationwide basis. In general, innovative projects with international growth opportunities are prioritized. The grants also co-finance socioeconomically profitable projects that are important for reaching political goals in the region, and that would not be realized to the same extent without government loans or grants. IN awards development grants to small and medium enterprises (SMEs) that have the competence, ability and capacity to meet the necessary requirements in creating innovative solutions for the market. Profitable projects that are financed include building facilities, modernizing or restructuring businesses, further business development or establishing presence in new markets. It is also possible to apply for financial support for the planning phase of the projects. This could be to document the potential growth opportunities pertaining to a project (Innovation Norway, 2016f).

Selection Criteria

For a project to receive the development grant, it needs to represent a novelty in the market. The applicant must present realistic plans and budgets, and the project must increase the company's profitability. IN also assesses the company's relationships to stakeholders who are crucial to the existence of the business, as well as the company's debt collaterals and its ability to repay debt. The size of the grants vary depending on how much is needed to trigger the projects, as well as governmental regulatory limitations (Innovation Norway, 2016g).

The intention behind the development grants is to relieve risk, compensate for market failure and to ignite the process of initiating research and development projects that involve some risk.

The support for research and development could be increased by 15% if there is a cooperation between two independent parties, where one of the parties is an SME with less than 250 employees. Smaller businesses will often get a larger portion of the capital need financed by IN in comparison to larger firms. Many development projects only include experimental development or prototyping. In experimental prototyping or development, the business is using known science, technology or commercial knowledge, with the intention of creating new, improved products, production methods or services. These projects need to have a documented potential for growth in either domestic or international markets (Innovation Norway, 2016g).

Measuring Growth

Growth in firms is important to job creation and value creation, which are important objectives for innovation Norway. A large part of literature on growth in small businesses defines growth in terms of employment (David, 1994; Schutgens & Wever, 2000; Hoogstra & van Dijk, 2004). This is due to policy makers' interest in job creation in society. A growing number of employees can indicate increased activity for the business, thus signaling further growth opportunities. However, one cannot measure companies' growth solely by the number of employees they have. In this study, we measure growth by various parameters. In addition to number of employees, we measure growth in sales revenue, value creation, operating profits and return on assets.

We have included growth in sales as an outcome variable since generating revenues is crucial for businesses. Sales should represent the foundation of a business and it is considered as the least subject to manipulation (Kinserdal, 2008). It consists solely of revenues from selling products or services, and is an indication of a company's state at its core. We also measure growth in value creation, defined as salary costs and operating profits combined (Oxford Research AS & Møreforskning Molde AS, 2014). As enhancing value creation is part of IN's primary goal, measuring growth in value creation is an important criteria when evaluating IN's ability to reach their objectives. We also wanted to measure effects on profitability of IN support. We use operating profit as a proxy for profitability. We were interested to see if we could find any positive effects of treatment on profitability, as past research has not been able to establish this link (SSB, 2015a). To investigate the effects of treatment on how efficiently the companies can generate profits from their assets, we included return on assets as an outcome variable. According to Hagel, Brown, & Davison (2010), return on assets is a good measure of firm performance as it highlights the return on the assets required to run the business, while avoiding the potential distortions caused by financial strategies that can influence for example return on equity. To calculate return on assets we use ordinary results after taxes and not net income, as we do not want any extraordinary income or expenses to affect the results.

To calculate growth, compound annual growth rate (CAGR) would be preferable, as it describes growth relative to the base point. However, some of the outcome variables such as value creation and operating profits can shift from negative to positive values. Measuring the percentage growth by these parameters could provide meaningless statistics. Given the nature of our data, measuring growth in absolute numbers is more straightforward for all parameters. We therefore measure growth for the outcome variables in absolute numbers, and compliment this by presenting CAGR where the effects of treatment are significant. To examine relative measures of growth, we also investigated growth using certain ratios to evaluate treatment effects. We therefore measure treatment effects on value creation per employee, sales per employee and operating profits per employee. These performance measurements can be good proxies for measuring productivity, and they can also form good alternatives to return on assets for technology based companies with a limited amount of assets. We also measure return on sales, computed as operating profits divided by sales, to evaluate treatment effects on operational efficiency (Albrecht, Stice, Stice, & Swain, 2010).

Data

In this section, we present the data sources used, the information it contains, and how the data has been processed. The data used for the analyses was collected from four data sources. The Norwegian Social Science Data Services (NSD) provided data on all 35,724 firms that received any type of support from IN in the years 2006 to 2010. From these firms, 3,459 received establishing grants, and 6,264 received development grants. Moreover, we received data from IN on all the 7,510 rejected applications for IN support in the same period that were available in their database. From these rejected applications, 1,863 firms had a different application approved from 2006 to 2010 and were therefore excluded. This left us with 2,544 rejected applications for the establishing grant, and 934 rejected applications for the development grant. The distribution of the treatment status for each year, for both grants, is displayed in table 1 below.

Table 1: Distribution of treatment status by grants and year

	Establishing grants			**Development grants**		
Year	Untreated	Treated	Total	Untreated	Treated	Total
2006	541	663	1,204	174	1,377	1,551
2007	375	655	1,030	122	1,251	1,373
2008	369	638	1,007	126	1,223	1,349
2009	609	828	1,437	266	1,189	1,455
2010	650	675	1,325	246	1,224	1,470
Total	**2,544**	**3,459**	**6,003**	**934**	**6,264**	**7,198**

The data on rejected applications for IN support included organization numbers, information on the type of support the companies applied for and the application year. However, it did not display the reason for rejection, something that would be interesting when discussing reasons for a potential deviation between the performance of the treated and untreated firms. The IN data included information on the type of support received by the firms, the year the application was processed and the number of employees in the year of processing. SNF provided us with full accounting statements and information from the industry database for all firms in The Brønnøysund Register Centre for the years 2006-2013. This made it possible to analyze growth using the accounting numbers for the firms researched. The accounting statements included key figures such as sales revenue, operating profit, size of assets, net income and value creation. From the industry database, we obtained qualitative information such as geographic location, industry and number of employees. The geographic location variables were counties aggregated as displayed in table 2 below.

Table 2: Aggregated geographic location variables

Region	Counties
Østviken	Østfold, Oslo, Akershus
Innlandet	Hedmark, Oppland
Vestviken	Buskerud, Vestfold, Telemark
Sørlandet	Aust-Agder, Vest-Agder
Vestlandet	Rogaland, Hordaland, Sogn og Fjordane, Møre og Romsdal
Trøndelag	Sør-Trøndelag, Nord-Trøndelag
Nord-Norge	Nordland, Troms, Finnmark

In order to use these extensive sources of data for analyses, we merged them in order to obtain panel data with repeated observations on the key figures from the firms' accounting statements and industry database. The databases were merged using either customer ID or organization number as a key, depending on the data available.

When preparing the analyses, we faced an important decision about when to measure the effects of IN support. One of INs main objectives is to assist in development of long-term and sustainable value creation, so we should measure the effects in the long-term as well. SSB (2015a) measures the effect three years after treatment in their report, which they base on discussions with IN. We chose to follow the procedure of SSB, and measure the effects three years after treatment for our main analysis, but in addition, we estimate effects two years after treatment to investigate more immediate effects of treatment. The latest available accounting data was from 2013. Accordingly, 2010 is the most recent year of treatment we analyze in our report. Since the purpose is to study post treatment dynamics, we only investigate firms with accounting and industry information available at least three years after assignment to treatment. We only include firms that are active three years after assignment to treatment. As seven out of ten startups do not survive the first five years after establishment in Norway, a great part of the sample regardless of treatment is lost when looking at the effects three years after treatment (SSB, 2015b).

Methodology

In the following sections, we will discuss the methodology applied for our analysis. When estimating treatment effects in an observational study, we face the fundamental evaluation problem of not being able to observe the counterfactual outcome for the treated firms, namely what had happened had they not been treated (Caliendo & Kopeinig, 2008). The treated firms might differ from the untreated firms as they are selected for treatment by IN based on some selection criteria. This selection bias creates a potential endogeneity problem, as firm growth potential is likely to correlate with application and selection for treatment. In order to compare treated with untreated firms, and justify causal interpretation of the results, we need the untreated firms to be as similar to the treated firms as possible (Angrist & Pischke, 2009).

With precise knowledge of the rules deciding treatment, regression discontinuity (RD) research design would be an applicable method of analysis (Angrist & Pischke, 2009). RD design entails comparing firms that have applied for support from IN and barely had their application rejected, with firms that applied and barely had their application approved. By comparing firms on both sides of a given cutoff point, the firms with rejected applications would likely be similar to the treated group. We would then be able to establish valid causal relationships between treatment and growth to a great degree. However, this method would require knowledge of a cutoff point for which firms receive treatment, and how the treated and untreated firms rank according to this cutoff point. Innovation Norway would not supply us with this data, making the RD design method infeasible.

However, Innovation Norway did provide us with data on firms that have applied for support and were rejected. This enabled us to match the treatment group with a control group of similar firms, as these businesses also have projects they wish to realize with the potential for growth that this implicates. Creating the counterfactual outcome for the treated firms is not possible in an observational study, but using matching is the closest we get to a natural experiment given the data available.

Matching Technique

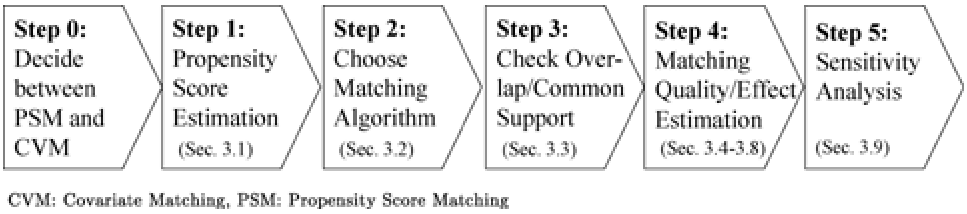

Figure 2: The five steps of propensity score matching.

According to Caliendo & Kopeinig (2008), there are five steps necessary when implementing Propensity Score Matching (PSM). In the following section, we will start with a brief discussion of matching as an econometric measure, before we clarify the five steps of PSM, as illustrated in figure 2 above.

The goal of the study is to estimate the average effect of treatment from IN. The observed difference in performance between treated firms and untreated firms equal the average effect of treatment on the treated, plus the selection bias. Matching involves pairing treated and untreated firms with similar pre-treatment characteristics. The technique corrects for selection bias, and isolates the effect of the treatment, enabling us to infer causality.

Step 0: Decide between Covariate Matching and PSM

We considered two possible matching methods to create a control group of comparable untreated firms for estimating treatment effects. The first was covariate matching, which involves exact matching on certain covariates to remove observable differences between the treatment and comparison group. This multidimensional method could potentially cause difficulty when we want to match along many different variables, as there are less firms suitable for matching the more complex the matching variables are. Furthermore, our analyses match on a handful of variables that take on a range of values. According to Gertler, Martinez, Premand, Rawlings, & Vermeersch (2011), this could lead to “the curse of dimensionality”, making it hard to identify two subjects that match along all these covariates.

Angrist & Pischke (2009) argue that the PSM technique solves this problem, as the matching unit from the control group does not need to have the exact same value for all observed covariates as the treated group. With PSM, you only match against a one-dimensional value, which is the conditional probability of treatment given the observed covariates. The propensity score is a single index value that ranges from zero to one, and it summarizes all the included observed characteristics as they influence the likelihood of treatment. PSM finds matches from the control group to distribute the measured covariates equally between treated and untreated firms. It also helps improve the precision of estimated treatment effects (Starks & Garrido, 2014). In our analysis, the control group of firms was significantly smaller than the treated group, so we chose to use PSM to avoid losing a substantial part of the sample due to dimensionality. Past research on the topic performed by SSB (2015a) has also used this technique. PSM is based on two assumptions. The first is the conditional independence assumption (CIA), which means that the value of the outcome variable is independent of treatment when we condition on propensity score. The second is the common support assumption, which ensures that treated firms are matched with untreated firms that have propensity scores slightly larger or less than those of the treated firms.

Step 1: Propensity Score Estimation

Caliendo & Kopeinig (2008) argue that using logit and probit models to estimate the propensity score usually yield similar results for a binary treatment case like the one we investigate. Based on Gertler et al. (2011), we used a probit model, as this study uses a probit regression to exemplify propensity score estimation. The probit model estimates the probability of treatment and how the included covariates affect treatment. When choosing which covariates to include in the PSM, the goal is to find covariates so that the outcome variable is independent of treatment, conditional on the propensity score. Only variables that simultaneously influence the assignment to treatment and the outcome variable should be included (Caliendo & Kopeinig, 2008). Angrist & Pischke (2009) recommend focusing on a small subset of all possible covariates chosen to predict both treatment and outcomes.

After talks with Innovation Norway, we realized geographic location, market potential, degree of innovation and feasibility are important factors in determining treatment. In the period our data comprises, IN prioritized certain industries, so industry was also important when assigning grants. Some of these factors are unobservable in our data, and thus not applicable for matching. We therefore include the observable characteristics geographic location, industry, size of assets and application year for matching.

The Norwegian government aims to stimulate the economy in certain geographic regions, particularly rural areas, and it has made access to financial support easier for businesses located in these areas (Frøyen & Rosenkilde, 2016). We therefore included the covariate indicating geographic location in the matching algorithm. We also included application year in order to compare companies that received funding under similar conditions, and in the same economic cycle.

Size of assets is an indicator of the size of the company, and affects the probability of treatment. Some firms might be too large to be eligible for certain types of grants. This is mainly due to article 53 in the competition rules of the EEA agreement, that prohibits agreements and conduct that distort and restrict competition (The EFTA Surveillance Authority). Based on this, we added size as a matching variable.

Previously, IN focused more on sectors such as the oil and gas industry, maritime industries, agriculture, tourism and healthcare. We have therefore matched companies from the same industry, as some of the industries have received significantly more funding over the years. Table 3 in the analysis section display that certain industries are overrepresented in regards to receiving treatment, thus making industry a good indicator of treatment. Industry is also likely to affect outcome, as growth rates typically varies by industry. To avoid matching firms that are very different in terms of technology and business, we believe that matching on industry is particularly important. We therefore implement exact matching on industry, complemented by the propensity score of the other covariates as a partial balancing score, as performed by Lechner (2002). Based on the small sample of untreated observations for some industries, we considered aggregating some of the industries into groups. However, we chose not to aggregate the industries to avoid matching firms from different industries.

After merging the data from the different data sources, we discovered that there were missing values for the covariate indicating geographic location. Rosenbaum (2010) argues that the propensity score remains well defined with missing covariate values, and that matching will balance the observed covariates and the missing covariates.

Step 2: Choose Matching Algorithm

There are several matching estimators applicable for PSM. All of these contrast the outcome of the treated firms with the outcome of the control group of untreated firms. The estimators differ by how the neighborhood for each treated individual is defined and how the common support problem is handled in regards to the weights assigned to the neighbors. There is no clear best choice of estimator for all situations, and the best option depends on the data at hand (Caliendo & Kopeinig, 2008).

Two commonly used matching estimators are Kernel Matching and local linear matching. These algorithms use a weighted average of all individuals in the control group of untreated firms to produce the counterfactual outcome. These methods produce lower variance than other methods, by using more information. A drawback of these methods is that they could include observations that are bad matches (Caliendo & Kopeinig, 2008).

Nearest Neighbor (NN) matching is the most straightforward matching estimator (Caliendo & Kopeinig, 2008). NN matching entails a matching of the treated firms with the untreated firms that are closest in terms of propensity score. We emphasized finding good matches, and as there were few untreated observations compared to treated observations, we chose NN matching with one neighbor for our analysis. This matching technique faces the risk of having bad matches if the closest neighbor is too far away. To avoid bad matches, we impose a maximum tolerance level for the propensity score distance of the matches, a so-called caliper. This ensures that the nearest untreated firm falls within a pre-specified radius for a treated firm, securing that the common support assumption holds (Caliendo & Kopeinig, 2008).

We allowed replacement in the NN model to enable untreated individuals to be matched more than once. Firstly, since the sample of untreated individuals was significantly smaller than the treated, and secondly, to avoid having the order in which observations are matched influence the estimates. Matching with replacement is also advantageous as there are more firms with high propensity scores in the treated group than in the untreated group. If we did not allow for replacement, we could provoke some bad matches of high-score firms with low-score firms. This would lead to the exclusion of low-score firms due to our introduction of caliper. The choice of using replacement is also supported by Caliendo & Kopeinig (2008), who argue that it does not make sense to match without replacement if there are only a few untreated observations, as is the case in our study.

Step 3: Check Overlap/Common Support

A visual analysis of the propensity score distribution in both groups is recommended in order to check the region of common support (Caliendo & Kopeinig, 2008). We therefore produced graphs displaying the propensity score distribution by treatment status to investigate whether the common support condition holds for the sample in question.

Step 4: Matching Quality/Effect Estimation

The main purpose of PSM is to balance all covariates, as opposed to predicting the selection for treatment. After performing the matching, we examined whether the matching procedure was able to balance the distribution of the relevant covariates in both groups. The balance was evaluated by performing a t-test to check for significant differences in covariate means between the two groups. We also considered the standardized bias, which is the percentage difference of the sample means as a percentage of the square root of the sample variances in the two different groups (Leuven & Sianesi, 2003). If the covariates are not well balanced, Caliendo & Kopeinig (2008) suggests re-specifying the model until a balanced distribution of the covariates is obtained. However, since our choice of covariates was limited by the data at hand, we accepted that the covariates were unbalanced in some cases.

Step 5: Sensitivity Analysis

According to Gertler et al. (2011) it is considered good practice to check the robustness of matching results by using various matching algorithms. To examine the robustness of the estimated results, we also apply other matching estimators. We ran the analyses again using two different approaches. Firstly, we introduce oversampling, by using nearest neighbor matching with three neighbors (NN=3). This technique increases the bias by producing poorer matches on average, but it also reduces the variance, as more information is used to construct the counterfactual. Secondly, we implement Kernel Matching, which uses the weighted average of all untreated individuals to construct the counterfactual outcome. In our small sample of untreated observations, Kernel has the advantage of using all the information available, allowing it to produce lower variance. However, this could include observations that are bad matches. We also examined how sensitive the estimated results were to outliers in the data, by trimming the top and bottom 1 and 5 percent of the values of the outcome variables.

Differences-in-Differences

The conditional independence assumption for PSM requires that all covariates that influence treatment assignment and potential outcome simultaneously need to be observed by the researcher (Caliendo & Kopeinig, 2008). After discussions with IN, we realized there were several unobservable determinants for treatment and outcome. The differences-in-differences (DD) matching estimator relaxes the conditional independence assumption and allows for unobserved, constant over time differences in outcomes between the treated and untreated firms (Caliendo & Kopeinig, 2008). DD is a version of fixed-effects estimation using aggregate data. The application of the DD method relies on the assumption that the groups would have common trends in the absence of any treatment. (Angrist & Pischke, 2015). As seen in table 4, we have investigated this for development grants by looking at growth for the outcome variables in a three-year period prior to the processing of the application to IN. For establishing grants, pre-treatment growth was not estimated, as the sample available was too small. We return to this issue in the analysis section. If the common trends assumption holds, unobservable firm characteristics that differ between the treated and untreated firms do not influence the estimates. As long as they are time invariant over the 2-3 year horizon of our analyses, DD will still be valid (Gertler et al., 2011).

The DD method subtracts the pre-treatment difference between the treated and untreated firms from the post-treatment difference, thereby adjusting for the fact that the groups were not the same initially (Angrist & Pischke, 2009). This enables us to isolate the effect of the treatment. We focus on the average treatment effect on the treated (ATT) for the effect estimation, as this specifically focuses on the effects of treatment for those that the program is intended. The expected value of ATT is the difference between the expected outcome with and without treatment for those who applied for treatment (Caliendo & Kopeinig, 2008). Formally, the parameter we want to estimate with the DD estimator is $\gamma_{t+s} = (Y_{t+s}^{T} - Y_{t-1}^{T}) - (Y_{t+s}^{C} - Y_{t-1}^{C})$. The estimator compares the difference in the outcome variables of the treated firms T before treatment $t-1$ and after treatment $t+s$ with the control group of untreated comparable firms C. The parameter is obtained by estimating the regression model below.

$$Y_{it-1,t+s} = \beta_0 + \beta_1 Treated_{\mathrm{i}} + \beta_2 Post_{t+s} + B_3 Treated_{\mathrm{i}}\ x\ Post_{t+s} + \varepsilon. \quad (1)$$

$Y_{it-1,t+s}$ is the outcome variable. $Treated_{\mathrm{i}}$ is a dummy variable equal to 1 if the observation is treated. It controls for constant differences in the outcome variable between the treated firms and the untreated firms before treatment. The variable $Post_{t+s}$ is a dummy variable taking the value 1 for post-treatment period $t+s$ and 0 in pre-treatment period $t-1$. It controls for aggregate period effects that are common for the two groups. The term $Treated_i\ x\ Post_{t+s}$ is an interaction term between $Treated_{\mathrm{i}}$ and $Post_{t+s}$. Its coefficient B_3 represents the DD estimator of the effect of treatment on the treated firms, and this is the causal variable of interest in our study, i.e. $B_3 = \gamma_{t+s}$ (Bandick & Karpaty, 2007).

The sample includes data on companies that have received treatment from IN several times. This will likely lead to a violation of the assumption of independently and identically distributed error terms, as there is likely to be within-firm correlation for the repeatedly treated firms (Guan, 2003). To correct for this serial correlation, we clustered the standard errors within firms. According to Angrist & Pischke (2009), clustered standard errors are unlikely to be reliable with few clusters. Nevertheless, there are many clusters in our sample, since receiving several treatments is regular.

Analysis

In this section, we present the results from the analyses. Firstly, we display some descriptive statistics. We then discuss how the included covariates affect the probability of treatment and whether the common support assumption holds. In addition, we evaluate the balance of the covariates in the matched sample to see that the treated and untreated firms are comparable with respect to these covariates. Lastly, we display and discuss the estimated treatment effects on growth and profitability.

Descriptive Statistics

In table 3 below, we display the distribution of treatment status by industry for the firms included in the analyses. As the treated sample is larger than the untreated sample, there is a majority of treated firms for all industries. For establishing grants, there are no untreated observations for primary industries in the data at hand. For development grants, the same applies for shipping and finance/insurance. We exclude these industries from the respective analyses, as we perform exact matching on industry.

Table 3: Treatment assignment by industry and type of grant

Industry	**Establishing Grants**			**Development grants**		
	Untreated	Treated	Total	Untreated	Treated	Total
Primary Industries	0	9	9	2	104	106
Oil/Gas/Mining	1	1	2	1	20	21
Manufacturing	12	109	121	36	685	721
Energy	3	9	12	3	29	32
Construction	7	14	21	6	64	70
Commerce	28	65	93	11	149	160
Shipping	2	3	5	0	21	21
Transportation/Tourism	5	20	25	10	137	147
Telecommunications/IT/Media	54	177	231	20	189	209
Finance/Insurance	1	6	7	0	37	37
Real Estate Services	6	13	19	25	147	172
Services	67	330	397	20	751	771
R&D	5	45	50	2	127	129
Public Sector/Culture/NGOs	19	83	102	18	303	321
Total	**210**	**884**	**1,094**	**154**	**2,763**	**2,917**

Pre-Treatment Growth

As discussed in the methodology section, an important assumption for DD estimation is that the groups compared would have common trends in the absence of any treatment. To investigate whether this assumption holds, we compared outcomes for the treated and untreated firms before the application was processed, as suggested by Gertler et al., (2011). We looked at growth for the outcome variables starting from four years before the processing year until the year before the processing. This implies that if e.g. 2006 is the year the application was processed, we would look at the growth from 2002 to 2005. We chose this period to rule out any treatment effects in the year of processing for the companies that received treatment. For the variables operating profit and value creation, we calculated growth in absolute numbers as the values for these two variables can shift from negative to positive or vice versa, thus providing meaningless statistics when looking at growth numbers. The growth rates are computed as annual growth rates. As most of the firms that applied for establishing grants are younger firms, only a few of these had available accounting information four years back. Even two years before the processing year, there were few firms with available accounting information. The sample of applicants for establishing grants was therefore too small to produce reliable numbers for pre-treatment growth. Consequently, we could not test whether the common trends assumption holds. As development grants are given to established firms, there were a lot more firms with available accounting information for calculation of pre-treatment growth.

Table 4: Annual pre-treatment growth by treatment status for development grants

Outcome variable	Treated		Untreated		Difference
	Sample	Annual Growth	Sample	Annual Growth	
Sales Revenue	2,047	1.71%	155	0.45 %	1.26%
		(12.8)		(1.64)	
Value Creation	2,331	1,569	187	919	650
		(10,584)		(3,771)	
Operating Profit	2,331	212	187	186	26
		(8,002)		(2,235)	
Number of Employees	1,619	0.15%	123	0.13%	0.02%
		(0.76)		(0.54)	

Standard errors in parentheses

Table 4 shows pre-treatment growth for all firms that applied for development grants from 2006 to 2010. Considering the large standard deviations, there is no clear indication of systematic differences in growth for the outcome variables. Growth in absolute numbers for value creation and operating profits is higher for the treated group. However, when looking at the compound annual growth rates from the mean values of the groups, the growth is slightly higher for the untreated firms. The growth rates for sales are sensitive to outliers, and when trimming the top 1 percent of the sample, the annual growth rate for treated firms is 0.61 percent and 0.44 percent for untreated firms. We thereby conclude that the pre-treatment growth is not significantly different for the treated and untreated firms, which supports that the common trends assumption required for the DD method holds. However, it is likely that Innovation Norway approves the applications that by their judgments have larger potential for growth. This could imply a larger growth rate for the treated firms, even in the absence of treatment. This counterfactual outcome is unobserved, so we cannot confidently conclude whether the common trends assumption holds for the years following treatment.

Probability of Treatment

The probit models displayed in table 9 and 10 show the estimated probability of receiving treatment versus not receiving treatment, based on the included covariates. We use the estimated probability of treatment to pair firms with similar probabilities of treatment. The probit model in table 9 for establishing grants shows that the likelihood of treatment increases with the size of assets and if the firm is from primary industries. Companies from the industries construction and commerce, as well as companies from locations Oestviken and Vest_Viken, are less likely to receive the establishing grant.

The probit model in table 10 for development grants shows that the likelihood of receiving IN support also increases with size of assets for development grants. Firms from the industries manufacturing, commerce, services, primary industries, R&D, transportation/tourism, telecommunications/IT/media and the public sector/NGOs are more likely to receive development grants. The industry variable shipping predicts treatment perfectly, and the observations from the shipping industry are consequently excluded from the analysis. Firms from Vestlandet, Innlandet and Vest_Viken are less likely to receive development grants.

Both probit models show that many of the dummy variables indicating industry and location are not significant in determining treatment. This makes them questionable fits for our models according to PSM theory. We chose to include them anyway as we believe these are important to contrast the outcome of comparable companies, because industry and geographic location are important factors in determining potential for growth and profitability. This is very clear today, as certain industries and regions in Norway are struggling due to relatively low oil prices, other exporting industries thrive due to a weakened Norwegian krone. The covariates in the model were also chosen according to their presumable importance for the creation of a group of untreated firms that comes from the same economic environment as the treated firms.

The Matched Sample

Tables 11 through 16 display the balancing properties after matching for the different analyses. The balancing tables and common support graphs are equal for the analyses on value creation (VC), operating profits (OP) and sales revenues (SR), as the firms in the matched sample are equivalent for all of them. For the analyses on growth in number of employees and return on assets, there are separate tables and graphs, since the matched sample is different. This is due to differences in the availability of data. The sample is matched strictly on industry, complemented by matching on the propensity score of the other covariates as a partial balancing score.

The variables for size and application year in table 11 for the establishing grant fulfill the balancing condition for VC, OP and SR. Several of the dummy variables indicating geographic location are not well balanced. However, the matching has reduced the mean bias considerably, and the overall balance is good. For the analysis on number of employees, we see from table 12 that Vest_Viken and application year are not well balanced. Nevertheless, the overall balance is good, and matching reduced the mean bias substantially. For return on assets, table 13 shows that the matching has reduced the mean bias only slightly, and the variables Oestviken, Troendelag and Innlandet are unbalanced. The overall sample is also not fully balanced.

As seen in table 14, the covariates in the analysis of development grants on VC, OP and SR are not perfectly balanced. In particular, the geography variables are unbalanced. Although the matching reduces the mean bias of the sample, the overall sample is still not perfectly balanced. For number of employees and return on assets, tables 15-16 show that the matching reduces mean sample bias substantially. Nonetheless, some of the dummies indicating geography are still unbalanced, causing imperfect overall balance for both analyses.

As we can see from figure 3 through 8 in the appendix, the mean propensity scores are quite high for both establishing grants and development grants. This is because the sample of treated firms is larger than the sample of untreated firms, which increases the chance that a given firm is treated. The distribution of propensity scores for the treated and untreated firms seem to overlap quite well for both grants, although the propensity scores are slightly higher for the treated firms. As we performed exact matching on industry, industries with only treated firms were outside of the common support region, and therefore excluded from the analysis. Based on these results, the assumption of common support seems to hold for the sample in question.

The primary analysis was performed using the matched DD estimator with one nearest neighbor matching (NN=1). The analyses on one nearest neighbor are performed with clustered standard errors, clustering on firm level. The number of unique observations for the analysis with one nearest neighbor is displayed in the results to demonstrate the number of unique untreated firms in the matched sample. The number of unique observations for the other matching techniques can vary slightly. However, the total number of matched firms in the analysis is always equal to the number of treated firms (or larger, in the case of matching with three nearest neighbors) as some firms are matched several times.

To examine the treatment effects of IN support on growth and profitability in the years following treatment, we estimate the regression model in equation (1), on the outcome variables displayed in the table below. The outcome variables display the mean differences-in-differences between the treatment and untreated firms. With the exception of the analyses on number of employees and return on assets, all numbers in the table below are in NOK 1,000.

Establishing Grants

Table 5: In the following table, we report the regression coefficients from the OLS regressions on various outcome variables. The coefficients represent total differences in growth in the outcome variables between treated and untreated firms, in the first 2-3 year interval after assignment to treatment. The left column displays the matching procedure applied in each case. Standard errors are displayed in parentheses. For NN=1 matching, standard errors are clustered at firm level. One, two or three asterisks imply that the coefficients are significant at the 10%, 5% or 1% levels respectively.

Matching procedure	Outcome Variables				
	(i)	(ii)	(iii)	(iv)	(v)
	Value Creation NOK 1,000	Operating Profits NOK 1,000	Sales Revenue NOK 1,000	Number of Employees Units	Return on Assets Percentage point (PP) change
NN=1 After 3 years	-73.70	-145.4	-871.6	0.282	-0.612
	(193.8)	(143.8)	(724.1)	(0.547)	(134.4)
NN=3 After 3 years	-86.44	-12.38	-1,056***	-0.499	-30.91
	(142.5)	(107.7)	(360.1)	(0.365)	(49.52)
Kernel After 3 years	-114.4	-23.57	-999.1**	-0.092	-15.72
	(135.4)	(97.65)	(440.0)	(0.339)	(45.10)
NN=1 After 2 years	87.97	-304.5**	1,105	0.174	151.7
	(198.7)	(127.2)	(734.2)	(0.386)	(234.4)
Unique observations					
Untreated	165	165	165	121	144
Treated	872	872	872	778	761

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In this section, we display and discuss the results from the analysis on the establishing grant. Based on the analysis, we find no evidence that the establishing grant have positive effects on value creation, number of employees or return on assets for treated firms compared to untreated firms.

For operating profits, the untreated firms perform significantly better than the treated firms group as seen in table 5 column (ii), with a negative effect of treatment on operating profits of NOK 304,500 two years after treatment. The result is significant on a 5 percent level. Trimming of outliers does not alter the conclusions. Although the estimated coefficients for operating profits are still negative after three years, they are no longer significant.

Using nearest neighbor matching with three neighbors or Kernel matching, we see from table 5 column (iii) that there is a negative effect of treatment on sales revenues. The results are significant on a 1 percent level and 5 percent level respectively. The results are robust to the trimming of outliers for both matching procedures. The sales revenue has on average increased by between NOK 1,056,000 and NOK 999,100 less in treated firms relative to untreated firms. However, for nearest neighbor matching with one neighbor the result is not significant and does not alter when trimming outliers. NN matching with one neighbor incorporates clustered standard errors, so this could indicate that within-firm correlation for the repeatedly treated companies is causing the significant negative results. Performing the analysis without clustered standard errors reduces the variance, but the estimated coefficient is still not significant at any reasonable level of significance.

Table 6: In the following table, we report the regression coefficients from the OLS regressions on various outcome variables. The coefficients represent total differences in growth in the outcome variables between treated and untreated firms, in the first 3 year interval after assignment to treatment. The left column displays the matching procedure applied in each case. Standard errors are displayed in parentheses. For NN=1 matching, standard errors are clustered at firm level. One, two or three asterisks imply that the coefficients are significant at the 10%, 5% or 1% levels respectively.

Matching procedure	Outcome Variables			
	(i)	(ii)	(iii)	(iv)
	Value Creation per employee NOK 1,000	Operating Profits per employee NOK 1,000	Return on sales PP change	Sales Revenue per employee NOK 1,000
NN=1 After 3 years	-9.289	-82.26	-130.3	-115.6
	(80.80)	(81.42)	(109.7)	(289.0)
Unique observations				
Untreated	121	121	165	121
Treated	778	778	872	778

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As seen in table 6, we find no evidence of positive treatment effects in regards to return on sales and value creation, operating profit and sales revenue per employee.

The results of the analysis on the establishing grant is in line with Oxford Research (2014), which also did not find any significant treatment effects of the establishing grant. There are several potential reasons for why the treated firms do not outperform the untreated firms. One of the reasons could be that some firms are given feedback on the likelihood of receiving financial support after a screening process by IN. Some of the firms with unviable business ideas that are the least eligible for financial support might refrain from applying, and will thereby not appear in our sample. Another reason why we are not able to prove any treatment effects might also be due to the quality of the data and size of the sample of untreated firms. By having a small sample, the mean values of the outcome variables are very sensitive to outliers.

IN rejects applications for support based on other criteria than the ability to implement the idea, level of innovation and the potential for value creation. These reasons for rejection could be that the applicants are in such a good state financially that IN would not have a triggering effect in realizing the projects, or that there would be competitive distortion caused by the support. It would be advantageous to have data on the reason for rejection of the application. We could use this to perform analyses on different subsamples of untreated firms. In addition, untreated companies may have received funding from external investors, who could provide knowledge and experience, as well as capital. There are also other forms of government financial support, such as tax reductions or funds from The Research Council of Norway, which the untreated firms could have received. The untreated firms may also perform well realizing their idea on their own, despite being rejected by IN, thereby increasing the mean growth of the untreated group.

Another potential reason why there are no evident positive effects of the establishing grant is risk. IN allocates the grant where there are no other forms of capital attainable for the entrepreneur to proceed with his or her business venture. There might not have been an adequate assessment of the market and the demand for the product, and the product or service might not commercialize well. The high risk associated with the businesses that receive the grant also affects the probability of success. IN’s focus on creating more entrepreneurs may come at the expense of their objective of creating quality entrepreneurs. Entrepreneurs wanting to open non-innovative businesses such as regular bakeries might not receive support due to the low level of innovation. However, a bakery might be more likely to succeed, than an innovative business with unknown commercial potential. This could translate into a higher probability of success compared to the high-risk IN supported businesses.

The analysis does not distinguish between financial support in phase 1 and phase 2. From our interviews with IN personnel, we learned that the threshold for qualifying for phase 1 funding is relatively low. The entrepreneurs do not need to confirm that their business is commercially viable, but rather that there are indications of a market based on preliminary analyses. Phase 1 supported firms might therefore receive funding based on an idea that may not be commercially viable. This could in turn explain why these firms do not grow faster than the untreated firms. Although untreated firms did not receive funding, they still might have received non-financial support from IN. Mentorship, competence programs and network might be more important than money for many entrepreneurs (Frøyen & Rosenkilde, 2016). If the untreated firms have received one or several of these forms of non-financial support, this could have enhanced their growth and profitability. Many of the recipients might also not know how to use the funding as efficiently as possible. Despite of already having a somewhat established business, mismanagement of resources might be an issue, as startups often have fluctuating expenses with a restricted amount of resources. A future study looking at the effects of non-financial IN support could be interesting to test the hypothesis that non-financial support is more important to entrepreneurs.

Unsuccessful priorities, lack of competence, and bad selection criteria on IN’s side could also be contributing factors to why the treated firms do not perform better than the untreated firms. One of the priorities that could be in conflict with IN’s main objective of enhancing value creation is their focus on creating jobs in the districts and rural areas. The focus on rural areas could lead to the awarding of grants to rural businesses with limited growth potential. Furthermore, there is a chance that the size of the grants, especially in phase 1 where they typically are 50,000-100,000 NOK, are too small to be of any significant difference for the growth of the businesses in the subsequent years. A possible solution to this could be to increase the amount of support to each idea, and support fewer ideas. This proposed solution is in conflict with IN’s recent changes, where they have reduced the maximum amounts of funding for the establishing grants. However, based on the results of the analysis, the size of the phase 1 grants might be too small to have a real effect on employment and growth. As previously pointed out, a lack of ability to choose successful businesses could be an important factor. IN could therefore consider using external expertise in the selection process, such as private equity firms, in order to help improve their performance (Andreassen, 2015)

A combination of the factors mentioned, with emphasis on the high risk IN takes and the small size of the phase 1 grants, could explain why the treatment effect on operating profits and sales revenues for the treated firms is negative. However, the sample in our analysis is small, and it could be biased by the fact that some applicants that received negative feedback on their idea chose not to apply. One should therefore be careful before drawing conclusions for the population of applicants for the establishing grant based on the analysis.

Development Grant

Table 7: In the following table, we report the regression coefficients from the OLS regressions on various outcome variables. The coefficients represent total differences in growth in the outcome variables between treated and untreated firms, in the first 2-3 year interval after assignment to treatment. The left column displays the matching procedure applied in each case. Standard errors are displayed in parentheses. For NN=1 matching, standard errors are clustered at firm level. One, two or three asterisks imply that the coefficients are significant at the 10%, 5% or 1% levels respectively.

Matching procedure	Outcome Variables				
	(i)	(ii)	(iii)	(iv)	(v)
	Value Creation NOK 1,000	Operating Profits NOK 1,000	Sales Revenue NOK 1,000	Number of Employees Units	Return on Assets PP change
NN=1 After 3 years	3,805	2,305	530.4	10.13***	-68.01*
	(2,568)	(1,981)	(5,646)	(3.541)	(36.51)
NN=3 After 3 years	4,195	2,386***	5,749	9.681***	-64.90*
	(2,731)	(714.8)	(7,301)	(3.181)	(35.85)
Kernel After 3 years	4,065	2,520***	2,480	8.578**	-60.42*
	(2,667)	(694.0)	(7,056)	(3.693)	(33.52)
NN=1 After 2 years	296.3	871.8	-2,804	9.363***	120.3
	(2,044)	(1,663)	(6,221)	(2.901)	(79.70)
Unique Observations					
Untreated	131	131	131	116	127
Treated	2,704	2,704	2,704	2,567	2,594

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

From Kernel matching and nearest neighbor matching with three neighbors, the operating profits for treated firms has increased by around 2.5 million NOK more, relative to untreated firms as seen in table 7 column (ii). The results are highly significant and robust to the trimming of outliers. However, the treatment effects on operating profits for nearest neighbor matching with one neighbor are not significant. The differences-in-differences estimator combined with NN matching with one neighbor is the only estimator that incorporates clustered standard errors. This could indicate that within-firm correlation for the repeatedly treated companies is causing the significant positive results. When not applying clustered standard errors, the results for nearest neighbor matching with one neighbor are significant on a 1 percent level, and the coefficient is similar to those obtained with three neighbors and Kernel. This indicates that within-firm correlation is influencing the results. The results are presented in absolute numbers. If we look at CAGR, the treated firms have had an annual growth in operating profits of 46.62 percent, while the untreated firms have had negative annual growth of 5.74 percent. If you trim the 1 percent largest and smallest observation, the annual growth in the treated group is 12.83 percent, while the growth for the untreated firms is still negative at 0.92 percent.

Firms that receive development grants increased employment by approximately 9-10 employees more than the matched firms during the 3 year interval after assignment, as seen in column (iv) of table 7. The result is highly statistically significant, and robust to the choice of matching method. The result is also robust to the treatment of outliers, although the estimated coefficients when trimming are slightly lower. When looking at compound annual growth numbers, the annual growth in number of employees is 13.13 percent for the treated firms and 0.22 percent for the untreated firms.

For return on assets, the coefficient is significantly negative on a 10 percent level. After looking more closely at the values for return on assets, we realized there were some outliers with a strong influence on the results. When we trim the outliers, the results are no longer significant. Using Kernel matching, the results are significant on a 10 percent level, but not robust to the treatment of outliers. For sales revenue and value creation, we find no clear evidence that development grants from IN have a positive effect on growth. However, all coefficients for value creation are positive, in line with the findings of SSB (2015a). This could indicate positive treatment effects of IN support on value creation.

Table 8: In the following table, we report the regression coefficients from the OLS regressions on various outcome variables. The coefficients represent total differences in growth in the outcome variables between treated and untreated firms, in the first 3 year interval after assignment to treatment.. The left column displays the matching procedure applied in each case. Standard errors are displayed in parentheses. For NN=1 matching, standard errors are clustered at firm level. One, two or three asterisks imply that the coefficients are significant at the 10%, 5% or 1% levels respectively.

Matching procedure	Outcome Variables			
	(i)	(ii)	(iii)	(iv)
	Value creation per employee NOK 1,000	Operating profits per employee NOK 1,000	Return on sales PP change	Sales revenue per employee NOK 1,000
NN=1 After 3 years	-224.6*	-94.36	32.90	-432.1
	(116.9)	(93.20)	(195.5)	(407.4)
Unique observations				
Untreated	110	110	115	110
Treated	2,022	2,022	2,461	2,022

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As seen in table 8 column (i), receiving development grants seems to have had a negative effect on value creation per employee. However, the coefficient is only significant on a 10 percent level, and the results are not robust to trimming of outliers. We find no evidence that development grants improve operating profits per employee, return on sales or sales revenue per employee, as displayed in table 8.

The results from the analysis are somewhat similar to the positive treatment effects on employment, sales revenue and value creation found by SSB (2015a). There are several possible reasons why the analysis shows significant positive treatment effects of development grants. The companies applying for the grant with already proven success might have a higher chance of receiving the grant, as IN only funds the best projects with the highest potential for value creation. These firms would also be able to use their internal resources, relationships and expertise to improve the profitably of the project. It is easier for successful companies to sell new products to existing customers, than it is for other firms that have to obtain new customers first (Daae, Sandberg, & Andreassen, 2015).

Along with the financial support of IN, the recipients of development grants normally also receive non-financial support from IN. This could include utilizing IN's international network or expertise for conducting a thorough market analysis, or receiving other advisory services and assistance in business development. This combination of financial and non-financial support could explain the improved the performance of treated firms relative to untreated firms. A reason for the higher growth in number of employees for the treated firms could be that the projects IN initiate often have a long time horizon, enabling the treated firms to hire employees for the duration of the project. However, one could question whether the awarding of the grant creates jobs in addition to the jobs that are financed by the grant itself.

Furthermore, IN might have chosen the right established businesses with growth potential. By performing a thorough analysis and selecting the most profitable companies, the chance of funding projects that will generate growth in operating profits. Having IN involved with a project could also attract more commercial capital, as funding from IN could reduce the risk for other investors. In addition, the untreated firms might not be able to finance their projects, and would therefore not grow at the same pace as the treated firms. Their projects, if conducted, may not have the same growth potential as those of the treated firms.

The positive treatment effects of development grants and lack of positive effects for the establishing grant indicate that IN should consider reallocating funds from establishing grants to development grants. This way IN could better align their funding with their overall goals of triggering successful business development and assisting development of value creation. Other academic papers also argue that established firms create more employment, and that only a very small number of startups manage to create significant growth (Reve, 2016; Daae, Sandberg, & Andreassen, 2015; Bjørnestad, 2015).

The validity of the results from the analysis on development grants is weakened by the quality of the data. The sample of untreated firms is very small compared to the sample of treated firms. This makes the mean values of the outcome variables for untreated firms very sensitive to outliers. It also raises doubts about whether we can draw conclusions about the population of applicants for development grants based on the analysis.

Limitations

Before applications arrive at IN for processing, many of the applicants attend courses or use the open phone line for entrepreneurs, where they can discuss their ideas with caseworkers. These offerings ensure that some of the applicants for the establishing grant have gone through a screening process prior to formally applying. Potential applicants can get feedback on their business idea during these courses, as well as information about the likelihood of receiving financial support. This could indicate that we have a selected sample, since potential businesses that have received negative feedback on their business idea, might choose not to apply. In that sense the business ideas that are the least eligible for support, might not appear in our sample of untreated firms. However, during the period of our study, these opportunities were less structured and happened less frequently than today (Frøyen & Rosenkilde, 2016). Furthermore, the course participants are not discouraged from applying. They are only given an indication of whether an application, given the information presented, would result in receiving financial support. Lastly, we lack information on how many entrepreneurs that refrain from applying after preliminary discussions with IN. Based on this, we cannot conclude whether there is a selected sample bias.

Several companies in the sample received treatment several times. Although we clustered the standard errors, the analyses does not correct for the fact that multiple treatments might contaminate the growth numbers for a firm. For instance, if a company is treated in 2006 and then again in 2007, 2008 and 2009, the growth numbers for 2006 might be contaminated by the subsequent treatments. Moreover, the analyses on establishing grants did not distinguish between phase 1 and phase 2 establishing grants. It would be interesting to see a future research on the topic that accounts for the difference between the two grants, as the amount of money granted for the two phases differ substantially.

DD attributes any differences in trends between the treatment and comparison groups to the treatment. If there are any other factors that influence the differences in trends between the two groups, the estimation will be biased or invalid (Gertler et al., 2011). A potential influential factor is that companies that have applied for financial support, regardless of outcome, might have received other forms of support. Either from IN or from other sources. The data does not disclose this, and these forms of non-financial support might affect firm growth. Moreover, we measure the average growth in the company as a whole for the included outcome variables. Companies receiving development grants are established firms, often involved in several businesses. The money granted by IN, however, is targeted for a specific project within the company. As we measure growth for the company as a whole, we cannot isolate the effect of the support. We can therefore not conclude with certainty that the common trends assumption holds for these firms. Ideally, we would control for these factors when estimating the treatment effects.

For firms receiving establishing grants, we could not investigate the pre-treatment growth properly, as these are young firms with limited available accounting information in the pre-treatment years. It is therefore not possible to say whether the common trend assumption required for the DD estimator holds. Additionally, the sample of matched untreated firms is quite small and the mean values of the outcome variables for these firms are sensitive to extreme values. The fact that some of these firms are matched with several treated firms enhances the sensitivity to outliers. This means that the values of the outcome variables for these firms are given more weight in the analyses. We attempt to control for this potential bias through robustness checks of our results by trimming the highest and lowest values of the outcome variable. In addition, we were not able to connect accounting data with data from Innovation Norway for all firms, some firms were excluded from the analysis. According to Rosenbaum (2010), this leads to a bias due to incomplete matching, raising questions about whether the study is still able to discuss treatment effects in the population of treated firms.

PSM produces matched samples of treated and untreated firms that on aggregate are balanced with respect to observed covariates. However, individual pairs of matched firms that are close on propensity scores may widely differ on specific covariates. This could lead to a comparison of firms with similar propensity scores that are not good matches. Nevertheless, the balance of the covariates should ensure that this does not lead to a noteworthy change in the results. We also do not have any information on why IN rejected the applications of the untreated firms. Among the rejected firms, there could be firms that have had strong business ideas with prospects of growth, but where IN would not have a triggering effect. These firms are likely to influence the mean growth of the untreated firms in a positive manner.

Conclusion

This paper examines the possible effects of government financial support to firms from Innovation Norway. To examine the treatment effects on growth, profitability and employment, we applied a propensity score matching technique with differences-in-differences estimation. Based on observable firm characteristics, we matched the treated firms with untreated firms that applied for support, but were rejected. By using the DD estimator, we also controlled for unobservable time-invariant fixed firm factors. We estimate the effects of treatment as differences in growth between treated and untreated firms, measured two and three years after assignment to treatment. The results are from an observational and not experimental context, so we cannot conclude that they necessarily represent causal effects.

Our analysis found no evidence that establishing grants have positive effects on growth and profitability. We even find some evidence of negative effects on operating profits two and three years after treatment from receiving establishing grants. The negative effects are not robust to the choice of matching method. There are also negative effects for sales, but these are not robust to the choice of matching method or the trimming of outliers. We find clear evidence that the development grant has positive effects on profitability and employment. The results for employment are robust and highly significant, while the results for operating profits are likely influenced by within-firm correlation, and thereby sensitive to the calculation of standard errors. Moreover, the small sample of untreated firms in the analyses raises doubts about whether o can draw conclusions about the population of applicants for IN grants based on the analysis.

IN's main goal is to trigger successful business development, and to assist the development of long-term value creation. The analysis gives no support that the establishing grant helps IN succeed in attaining this goal. Nor is there evidence that the establishing grant helps IN reach their secondary objective of developing more quality entrepreneurs. The development grants on the other hand, do succeed in attaining IN's secondary objective of creating expansive businesses, measured by the number of employees. The results do not allow us to conclude with certainty that the development grant contributes to IN's goal of assisting long-term value creation. However, the demonstrated positive treatment effect on number of employees, together with the indications of a positive treatment effect on value creation (also supported by SSB (2015a)), suggests that the development grant contributes towards the main goal. IN should therefore consider reallocating funds from establishing grants to development grants. This way IN could better align their funding with their overall goals of triggering successful business development and assisting development of value creation.

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Appendix

*Table 9: Probit model to estimate propensity score for the **establishing grant**. The estimated coefficients display how the included covariates affect the probability of treatment. A propensity score equal to 1 indicates 100% probability of treatment. Standard errors are included in parentheses. One, two or three asterisks imply that the coefficients are significant at the 10%, 5% or 1% levels respectively.*

Probit model to estimate propensity score	**Establishing grants**
Variables	Probability of treatment
Industri	0.447*
	(0.229)
Energi_VAR	0.0250
	(0.418)
Bygg_anlegg	-0.520*
	(0.294)
Handel	-0.390*
	(0.211)
Primærnær	0.522
	(0.650)
Olje_gass_gruve	-0.976
	(0.926)
Skipsfart	-0.209
	(0.478)
Finans_Forsikring	0.198
	(0.523)
FoU	0.480
	(0.299)
Transport_Reiseliv	0.0162
	(0.317)
Eiendom_Tjenester	-0.253
	(0.331)
Tjenesteyting	0.181
	(0.194)
Tele_IT_Media	-0.0247
	(0.199)
Offentlig_Kultur_NGO	-0.0905
	(0.220)
Nordnorge	-0.157
	(0.355)
Soerlandet	-0.0839
	(0.340)
Vestlandet	-0.219
	(0.145)
Oestviken	-0.416**
	(0.165)
Troendelag	-0.279
	(0.298)
Innlandet	0.151
	(0.327)
Vest_Viken	-0.347*
	(0.183)
Size	0.154***
	(0.0265)
Søknadsår	-0.166***
	(0.0354)
Constant	0.492*
	(0.252)
Observations	1,451

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Probit model to estimate propensity score for ***development grants****. The estimated coefficients display how the included covariates affect the probability of treatment. A propensity score equal to 1 indicates 100% probability of treatment. "Skipsfart" is excluded as it predicts treatment perfectly. Standard errors are included in parentheses. One, two or three asterisks imply that the coefficients are significant at the 10%, 5% or 1% levels respectively.*

Probit model to estimate propensity score	**Development grants**
VARIABLES	Probability of treatment
Industri	0.360***
	(0.112)
Energi_VAR	0.187
	(0.274)
Bygg_anlegg	0.0813
	(0.210)
Handel	0.270*
	(0.156)
Primærnær	0.738***
	(0.262)
Olje_gass_gruve	0.690
	(0.466)
Skipsfart	-
Finans_Forsikring	0.583
	(0.471)
FoU	0.850***
	(0.303)
Transport_Reiseliv	0.379**
	(0.172)
Eiendom_Tjenester	-0.126
	(0.140)
Tjenesteyting	0.832***
	(0.116)
Tele_IT_Media	0.271*
	(0.141)
Offentlig_Kultur_NGO	0.347***
	(0.129)
Nordnorge	-0.118
	(0.203)
Soerlandet	-0.0593
	(0.139)
Vestlandet	-0.336**
	(0.159)
Oestviken	0.255
	(0.171)
Troendelag	0.101
	(0.182)
Innlandet	-0.231**
	(0.105)
Vest_Viken	-0.334***
	(0.103)
Size	0.103***
	(0.0163)
Søknadsår	-0.155***
	(0.0240)
Constant	0.922***
	(0.157)
Observations	4,336

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Balancing Properties

Establishing Grant

Table 10: The table displays balancing of matching covariates for the analyses on ***value creation, sales revenues, and operating profits*** *for establishing grants. The t-test checks for significant differences in covariate means between the treated and control groups. For t values above 2 or below -2, the covariate is not well balanced. The mean bias below indicates the mean bias before and after matching, and is a good indicator for the reduction in bias achieved as a result of matching.*

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
Vestlandet	.10321	.11468	-3.6	-0.77	0.442	.
Nordnorge	.01491	.0195	-3.7	-0.74	0.462	.
Soerlandet	.0172	.02752	-8.3	-1.46	0.145	.
Innlandet	.02408	.04014	-13.6	-1.90	0.057	.
Oestviken	.05734	.07454	-7.2	-1.45	0.148	.
Troendelag	.0195	.00459	11.6	2.86	0.004	.
Vest_Viken	.04931	.04358	2.8	0.57	0.570	.
lsize	6.6115	6.6259	-0.9	-0.22	0.828	1.42*
søknadsår	3.3761	3.4151	-2.9	-0.59	0.552	0.87*

* if variance ratio outside [0.88; 1.14]

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.037	39.70	0.000	10.5	5.2	48.4*	1.08	0
Matched	0.010	23.88	0.004	6.1	3.7	23.2	1.57	100

* if B>25%, R outside [0.5; 2]

Table 11: The table displays balancing of matching covariates for the analysis on ***number of employees*** *for establishing grants. The t-test checks for significant differences in covariate means between the treated and control groups. For t values above 2 or below -2, the covariate is not well balanced. The mean bias below indicates the mean bias before and after matching, and is a good indicator for the reduction in bias achieved as a result of matching.*

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
Nordnorge	.01671	.01928	-1.9	-0.38	0.703	.
Soerlandet	.01928	.01671	2.0	0.38	0.703	.
Vestlandet	.11568	.13368	-5.4	-1.07	0.283	.
Oestviken	.06555	.06941	-1.6	-0.30	0.762	.
Vest_Viken	.05398	.03342	11.0	1.99	0.047	.
Innlandet	.02571	.0347	-7.2	-1.04	0.300	.
Troendelag	.02185	.01028	8.1	1.82	0.070	.
lsize	6.6485	6.7681	-7.8	-1.66	0.096	1.26*
søknadsår	3.2905	3.5077	-17.3	-3.27	0.001	0.89

* if variance ratio outside [0.88; 1.14]

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.067	56.34	0.000	14.0	6.4	66.0*	1.00	0
Matched	0.015	32.02	0.000	6.9	7.2	28.7*	1.41	50

* if B>25%, R outside [0.5; 2]

Table 12: The table displays balancing of matching covariates for the analysis on ***return on assets*** *for establishing grants. The t-test checks for significant differences in covariate means between the treated and control groups. For t values above 2 or below -2, the covariate is not well balanced. The mean bias below indicates the mean bias before and after matching, and is a good indicator for the reduction in bias achieved as a result of matching.*

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
Nordnorge	.01708	.0276	-8.0	-1.39	0.165	.
Soerlandet	.0184	.02497	-5.1	-0.88	0.379	.
Vestlandet	.11958	.09593	7.0	1.49	0.137	.
Oestviken	.07096	.04205	11.3	2.45	0.015	.
Troendelag	.02234	.00526	12.6	2.86	0.004	.
Innlandet	.0276	.04599	-14.6	-1.91	0.057	.
Vest_Viken	.05256	.03548	7.9	1.62	0.104	.
lsize	6.726	6.6031	7.9	1.78	0.075	1.52*
søknadsår	3.4231	3.5335	-7.8	-1.51	0.131	0.94

* if variance ratio outside [0.87; 1.15]

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.037	36.04	0.000	10.5	4.8	48.3*	1.16	0
Matched	0.014	29.32	0.001	9.1	7.9	27.6*	1.68	50

* if B>25%, R outside [0.5; 2]

Development Grants

Table 13: The table displays balancing of matching covariates for the analyses on ***value creation, sales revenues, and operating profits*** *for development grants. The t-test checks for significant differences in covariate means between the treated and control groups. For t values above 2 or below -2, the covariate is not well balanced. The mean bias below indicates the mean bias before and after matching, and is a good indicator for the reduction in bias achieved as a result of matching.*

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
Nordnorge	.03438	.0159	11.5	4.35	0.000	.
Soerlandet	.10536	.14085	-12.5	-3.98	0.000	.
Vestlandet	.05693	.08946	-12.5	-4.60	0.000	.
Oestviken	.09834	.03253	26.4	9.87	0.000	.
Troendelag	.05841	.05878	-0.2	-0.06	0.954	.
Innlandet	.20407	.22736	-5.7	-2.08	0.037	.
Vest_Viken	.20961	.30314	-21.2	-7.92	0.000	.
size	8.9128	8.7562	7.3	2.85	0.004	0.95
søknadsår	2.9006	2.7978	7.5	2.73	0.006	1.00

* if variance ratio outside [0.93; 1.08]

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.047	56.42	0.000	16.9	12.1	61.8*	1.01	0
Matched	0.038	285.63	0.000	11.6	11.5	46.6*	1.67	0

* if B>25%, R outside [0.5; 2]

Table 14: The table displays balancing of matching covariates for the analysis on ***number of employees*** *for development grants. The t-test checks for significant differences in covariate means between the treated and control groups. For t values above 2 or below -2, the covariate is not well balanced. The mean bias below indicates the mean bias before and after matching, and is a good indicator for the reduction in bias achieved as a result of matching.*

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
Nordnorge	.03584	.02104	8.9	3.19	0.001	.
Soerlandet	.10908	.08453	8.5	2.98	0.003	.
Vestlandet	.05921	.08804	-10.9	-3.96	0.000	.
Oestviken	.10245	.04908	20.7	7.26	0.000	.
Troendelag	.06116	.06116	0.0	-0.00	1.000	.
Innlandet	.20725	.26646	-14.5	-5.00	0.000	.
Vest_Viken	.20958	.31944	-24.7	-8.99	0.000	.
size	8.8756	8.7443	6.1	2.35	0.019	0.91*
søknadsår	2.9536	2.9622	-0.6	-0.22	0.827	0.95

* if variance ratio outside [0.93; 1.08]

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.051	54.84	0.000	17.2	12.2	65.0*	0.94	0
Matched	0.039	277.09	0.000	10.5	8.9	47.3*	1.51	50

* if B>25%, R outside [0.5; 2]

Table 15: The table displays balancing of matching covariates for the analysis on ***return on assets*** *for development grants. The t-test checks for significant differences in covariate means between the treated and control groups. For t values above 2 or below -2, the covariate is not well balanced. The mean bias below indicates the mean bias before and after matching, and is a good indicator for the reduction in bias achieved as a result of matching.*

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
Nordnorge	.03585	.01619	12.0	4.46	0.000	.
Soerlandet	.1091	.14264	-11.6	-3.65	0.000	.
Vestlandet	.05937	.09329	-12.9	-4.61	0.000	.
Oestviken	.10254	.0293	29.5	10.75	0.000	.
Troendelag	.06091	.06631	-2.4	-0.80	0.426	.
Innlandet	.21126	.22629	-3.6	-1.31	0.190	.
Vest_Viken	.21781	.32074	-23.1	-8.41	0.000	.
size	8.9501	8.839	5.2	1.99	0.047	0.95
søknadsår	2.899	2.8103	6.3	2.27	0.023	1.02

* if variance ratio outside [0.93; 1.08]

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.048	55.74	0.000	17.5	12.3	62.7*	1.06	0
Matched	0.042	304.26	0.000	11.9	11.6	49.1*	1.86	0

* if B>25%, R outside [0.5; 2]

Figures

Common support for the establishing grant

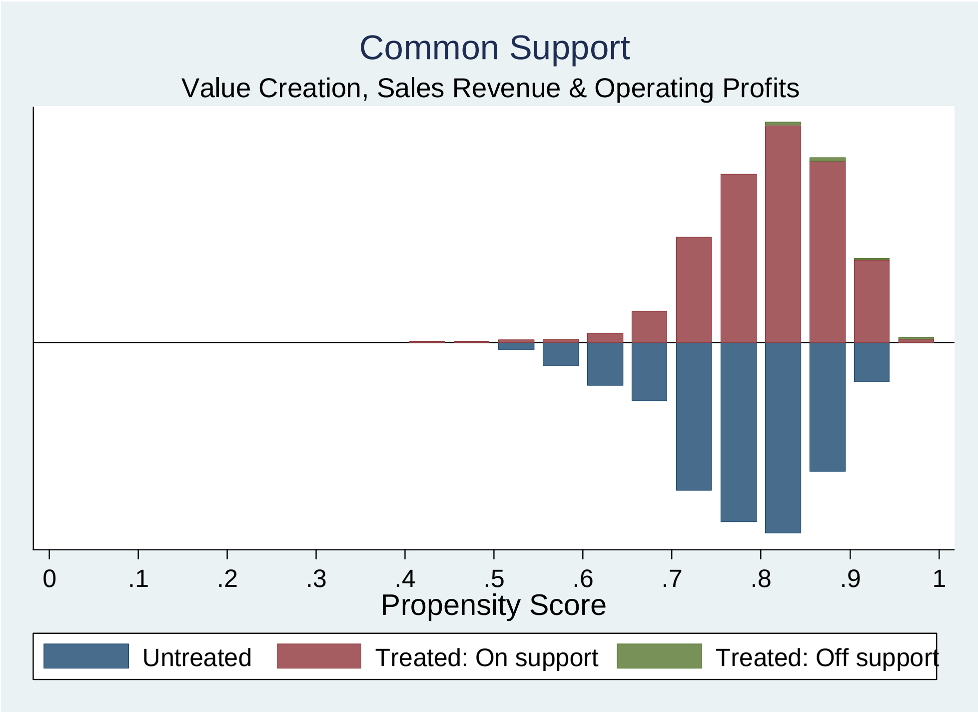

Figure 3: The histogram displays propensity score by treatment status for the analyses on value creation, sales revenue and operating profits for establishing grants. The treated: Off support observations are excluded from the analyses. The treated: On support are matched to untreated firms that are close in terms of propensity score in the analyses.

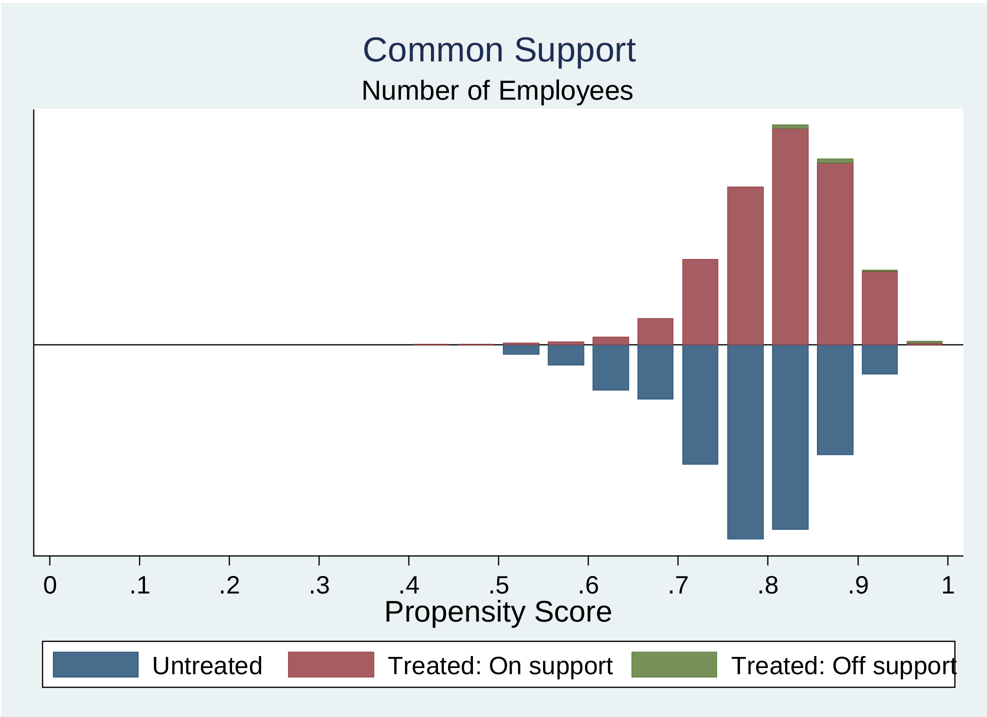

Figure 4: The histogram displays propensity score by treatment status for the analyses on number of employees for establishing grants. The treated: Off support observations are excluded from the analyses. The treated: On support are matched to untreated firms that are close in terms of propensity score in the analyses.

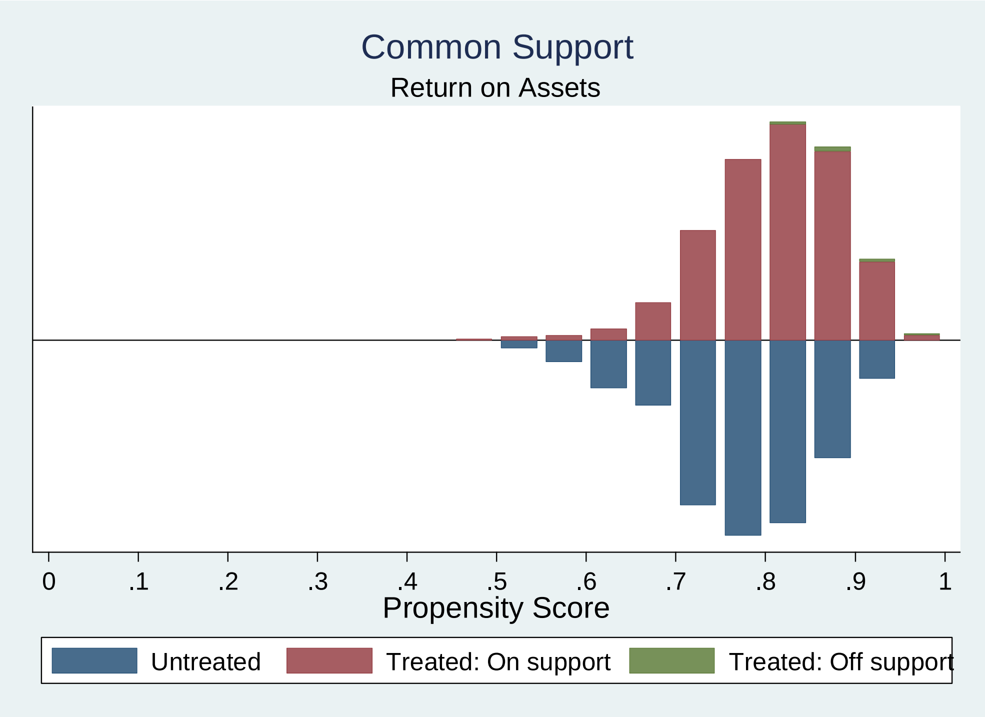

Figure 5: The histogram displays propensity score by treatment status for the analyses on return on assets for establishing grants. The treated: Off support observations are excluded from the analyses. The treated: On support are matched to untreated firms that are close in terms of propensity score in the analyses.

Common support for development grants

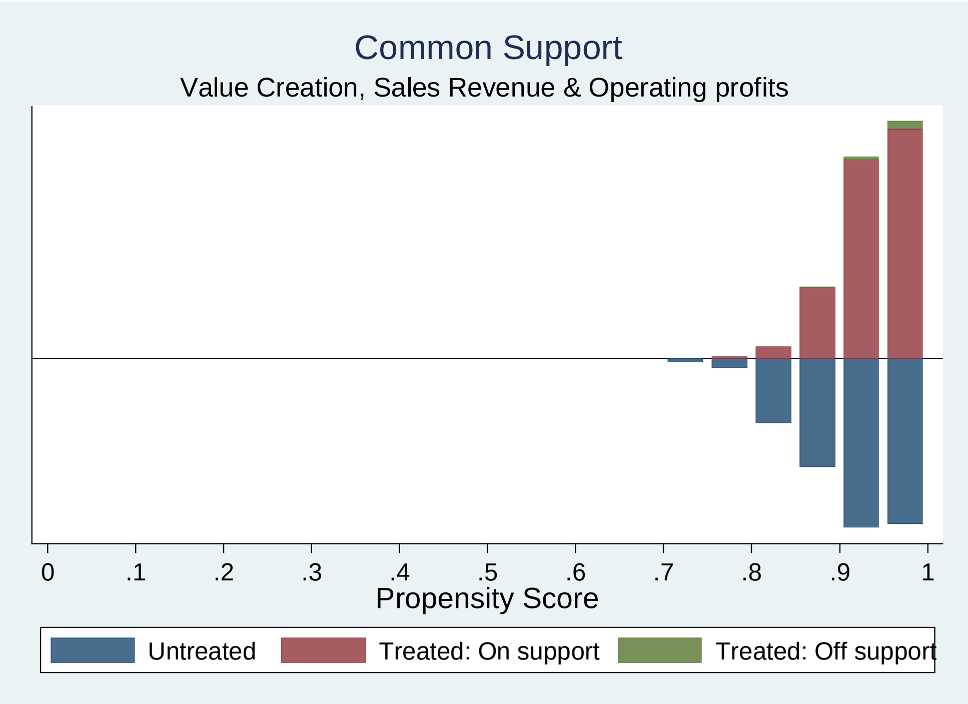

Figure 6: The histogram displays propensity score by treatment status for the analyses on value creation, sales revenue and operating profits for development grants. The treated: Off support observations are excluded from the analyses. The treated: On support are matched to untreated firms that are close in terms of propensity score in the analyses.

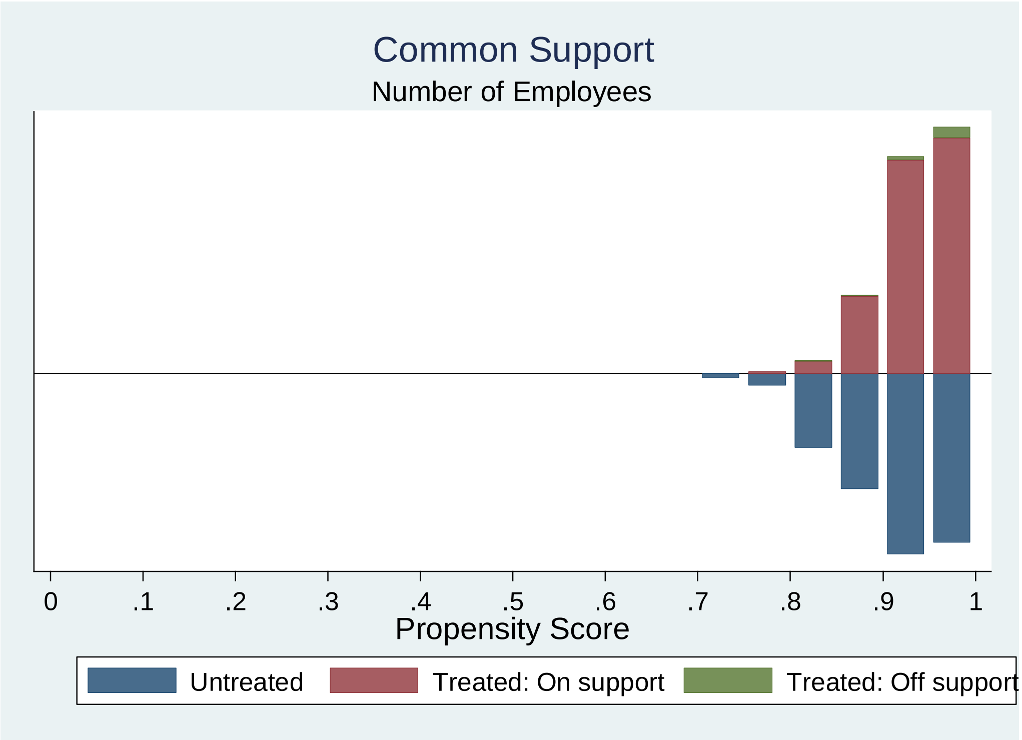

Figure 7: The histogram displays propensity score by treatment status for the analyses on number of employees for development grants. The treated: Off support observations are excluded from the analyses. The treated: On support are matched to untreated firms that are close in terms of propensity score in the analyses.

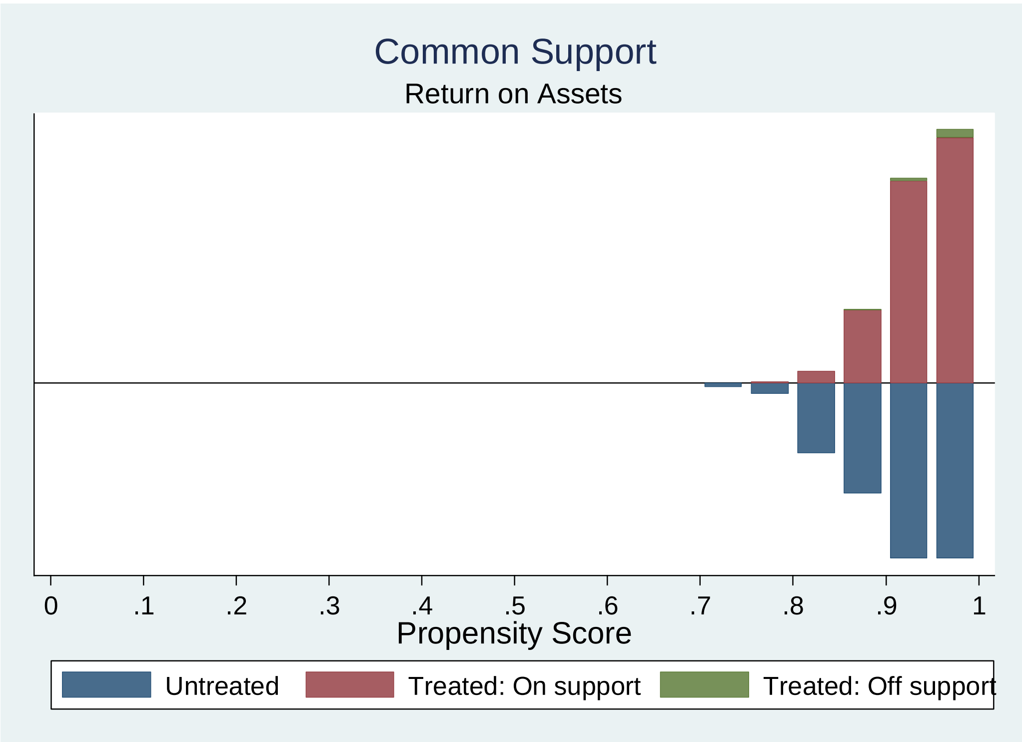

Figure 8: The histogram displays propensity score by treatment status for the analyses on return on assets for development grants. The treated: Off support observations are excluded from the analyses. The treated: On support are matched to untreated firms that are close in terms of propensity score in the analyses.

Stata code

```
*VALUE CREATION
use "M:\Master\Analyse resultater\Pischke_etablerer1.dta", clear
set more off

*Do a probit estimation to find out how the variables influence treatment probability
probit treatment Industri Energi_VAR Bygg_anlegg Handel Primærnær ///
       olje_gass_gruve Skipsfart Finans_Forsikring FoU Transport_Reiseliv ///
       Eiendom_Tjenester Tjenesteyting Tele_IT_Media Offentlig_Kultur_NGO ///
       Nordnorge Soerlandet Vestlandet Oestviken Troendelag Innlandet Vest_Viken ///
       lsize søknadsår

*PERFORM EXACT MATCHING ON INDUSTRY
probit treatment Vestlandet Oestviken Nordnorge Soerlandet Innlandet Vest_Viken ///
       Troendelag lsize søknadsår
predict double ps
g pscore2=.
*bransje is an industry variable that takes on values from 1-14, and the expression below
*thereby gives pscore2 values from 2-28, enabling exact matching on industry when we
*match within caliper in the matchin algorithm below
replace pscore2=bransje*2+ps

*Install user-written data package psmatch2
ssc install psmatch2, replace
*Make sure the sorting order of the data does not affect the results by random sorting
set seed 4486
replace u=uniform()
sort u
*NN matching with one nearest neighbor, we use the customized pscore2,and match within caliper
psmatch2 treatment, outcome(ValCre0 ValCre3) pscore(pscore2) neighbor(1) ///
       caliper(0.2)
*Check the balance of the covariates and the overall sample after matching
pstest Vestlandet Nordnorge Soerlandet Innlandet Oestviken Troendelag Vest_Viken ///
       lsize søknadsår, both
*Graph common support to see whether propensity scores overlap, specify pscore predicted
*from the probit model
psgraph, bin(20) pscore(ps)

*_id generates and the id of the match is stored in [_n1]. Use variable[_n1]
*to access the value of Kunde1 (customer ID) of obs [_n1]  */
sort _id
g str173 Kunde1_n1 = Kunde1[_n1]

drop _merge
*Merge in accounting data on outcome variables for the matched sample
merge m:m Kunde1_n1 using "M:\Master\Analyse resultater\matched_basedata_n1.dta"
keep if _merge!=2
drop _merge

*save dataset containing outcome data for the treated firms
save "M:\Master\Analyse resultater\angrist_approach_VC.dta", replace
*drop customer ID and rename it with control group customer ID in order
```

```
*to make this the data for the control sample. Drop outcome var treated group
drop Kunde1 ValCre0 ValCre3
rename Kunde1_n1 Kunde1
*generate variable to indicate that this is the control group
g treated=0
*duplicate dataset as observations for value creation in year0 and year3 are in the same
*observation, we want them to be separate in order to contrast them in a regression
expand 2, gen(Post)
*Generate new outcome variable containing outcome var for the control group
gen Valuecreation=.
replace Valuecreation=_ValCre0 if Post==0
replace Valuecreation=_ValCre3 if Post==1
*Save data on control group
save "M:\Master\Analyse resultater\angrist_approach_ctrl_VC.dta", replace

*Open data on treated group
use "M:\Master\Analyse resultater\angrist_approach_VC.dta"
*duplicate dataset as observations for value creation in year0 and year3 are in the same
*observation, we want them to be separate in order to contrast them in a regression
expand 2, gen(Post)
*gen var with same name as control group to indicate that this is the control group
g treated=1
*Gen outcome var containing outcome var with same name for the treated group
gen Valuecreation=.
* keep if _nn==1 indicates only values for treated group in matched sample are used
keep if _nn==1
replace Valuecreation=ValCre0 if Post==0 & _nn==1
replace Valuecreation=ValCre3 if Post==1 & _nn==1
*Append data on control group
append using "M:\Master\Analyse resultater\angrist_approach_ctrl_VC.dta"
reg Valuecreation Post##treated, vce(cluster Kunde_1)
```