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The Effect of Patents on Financial Constraints

An Empirical Analysis of Norwegian companies 2009-2018

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Abstract

In this thesis, we investigate the relationship between patenting activity and financial constraints for a broad panel of Norwegian companies between 2009-2018. The research is inspired by Hottenrott, Hall and Czaranitzki (2016).

Innovation is considered the key to sustained economic growth. It is however a commonly held belief among economists that R&D investments, and thus R&D active companies, are subject to financial constraints, in large due to asymmetric information. Facilitating for innovation is accordingly an important issue for countries seeking to secure and increase their future prosperity. A goal for the Norwegian government is to increase domestic R&D expenditure to three percent of annual GDP, and it is thus relevant how financial constraints in R&D active companies can be alleviated.

Patents have several characteristics that could make it an efficient tool for credibly conveying information and thus mitigate the information asymmetry between innovators and potential lenders or investors. Through a fixed effect regression model, we explore if physical investments in firms with a higher degree of patenting activity are less sensitive to internal liquidity.

The findings indicate that patenting activity does have a significant effect on financial constraints in small companies. Similar results are not detected for the full sample, medium or large companies. We do not find evidence supporting that the effect of patenting varies with firm age.

Keywords – Patents, Patent Applications, Research and Development, Financial Constraints, Information Asymmetries

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1 Introduction

Innovation has long been considered the key to sustained economic growth (Romer, 1990; Schumpeter, 1942). The historical increase in living standards can predominantly be attributed to innovation – particularly since the Industrial Revolution. In the latest decades, the significance of innovation has been reinforced by globalization, rapid advances in new technologies as well as the deindustrialization of developed countries (OECD, 2007). Facilitating for innovation is a fundamental challenge for countries seeking to secure and increase their future prosperity (OECD, 2015).

As Norway aims to move away from petroleum and shift towards a knowledge-based economy, developing domestic innovative capabilities is essential (NOU2016:3, 2016). In 2019 approximately 2.15 percent of the Norwegian gross domestic product was invested in research and development (R&D). This is lower than for all the other Nordic countries, as well as the OECD average (OECD, 2021). The biggest differences are observed in investments performed by the private sector. The Norwegian government does accordingly have an ambition to increase the domestic R&D intensity. In line with the EU, the target is to raise overall R&D investments to three percent of annual GDP (Norwegian Ministry of Education and Research, 2018). In order to achieve this goal, there is still a need for growth. Exploring tools and strategies that could stimulate Norwegian R&D expenditure is therefore of utmost interest.

It is a commonly held belief among economists that R&D investments are subject to financial constraints. One of the main causes for this is imperfections in the capital market, where information about the new invention is held asymmetrically between the inventor and potential lenders or investors (Hottenrott et al., 2016). This creates a challenge when assessing the quality of R&D projects, and obtaining credible information might present a substantial acquisition cost. Additionally, R&D projects often have a low collateral value, which increases the financial risk taken on by the lender or investor. Together these factors raise the cost of obtaining external capital for R&D active companies, in certain cases even to a degree where it is unavailable (Fazzari, Hubbard, & Petersen, 1988; Hottenrott et al., 2016).

Long (2002) suggests that patenting can mitigate this informational asymmetry. Instead of viewing patents merely as an instrument of privatizing information, one could argue that it is also an effective tool to credibly convey information. Patents and patent applications include detailed descriptions of the new technology, which generally will be approved or have been given a first assessment by an Intellectual Property Office. This is valuable and verifiable information to potential lenders and inventors, available at a relatively low acquisition cost. Furthermore, if market actors believe that patents are correlated with difficult-to-observe firm attributes, patents may work as a signal of said attributes. If patents do contribute to mitigating information asymmetries, it could also decrease the cost of external capital. This is the fundament of the theory that patenting activity contributes to alleviating financial constraints.

A multitude of studies have investigated the link between financial constraints and patents. Yet, the research is mostly conducted on start-up companies, and particularly in the context of venture capital. These studies predominantly find evidence that a relation between patents and financing does exist at an early stage. Similar research on companies beyond the start-up stage is however still limited, and especially so in a European context. Hottenrott et al. (2016) researched the phenomenon in established companies in the Flemish part of Belgium. They found evidence that patents do attenuate financial constraints on R&D investments also on a sample of more mature firms, but only for the smaller companies.

We want to investigate if a similar relationship may be established in a broad sample of Norwegian companies. We therefore aim to answer the following research question:

Does patenting activity affect financial constraints in Norwegian companies?

Our objective is to contribute to the research on the value of patenting, particularly for Norwegian firms. If patents help alleviate financial constraints they could work as a valuable tool in increasing R&D expenditure and thus promote innovation in several ways. To our knowledge similar analyses have neither been conducted in Norway nor in a Nordic country.

Norwegian regulations regarding patent and accounting data allow us to analyse an especially broad range of companies. The sample includes firms of all sizes, from a wide range of industries. We investigate a panel of 1224 Norwegian companies in the period 2009-2018. Through a fixed-effect model, we study how physical investment's sensitivity to internal liquidity responds to patenting activity.

The findings of the analysis indicate that a higher presence of prior patenting activity in small companies leads to less reliance on internal liquidity in order to invest. This implies that their patenting activity alleviates financial constraints. We have not found evidence for similar effects in medium or large companies. When analysing the effect of age we do not detect a significant effect of patenting activity on financial constrain in neither of the age subsets.

The current paper proceeds as follows: section 2 provides an outline of the Norwegian patent system, a theoretical background to the research question and the methodology, as well as a brief introduction to prior empirical evidence on the research field. In section 3 the hypotheses that will be investigated in the study are introduced. Section 4 presents the applied data, its origin, and how it is processed. Section 5 describes the econometric framework and methodical approach of the analysis. In section 6 the results are presented. In section 7 the implications and limitations of the findings are discussed. Finally, in section 8 we make the concluding remarks by summarizing the thesis's main themes.

2 Background

The following section provides a theoretical background to the research question. We begin with defining patents and describing the Norwegian patent system. This is followed by a description of how we define and measure financial constraints. Next, we discuss why R&D and R&D-active firms may be subject to financial constraints. Furthermore, the concept of patents as an instrument to alleviate information asymmetries is introduced. Conclusively, we give a brief introduction to prior empirical evidence on the relation between patents and financing.

2.1 Patents and the Norwegian patent system

A patent is a documented exclusive right granted for an invention (Altinn, 2020). Patents thereby provide an exclusive right to explore an invention commercially and prevent competitors from producing, importing or selling the patented technology. This could create the foundation for a competitive advantage. The protection is however timebound and restricted to the nations where the patent was obtained. The rights of the patent owner are also conditioned on public disclosure of the invention. The disclosure is intended to increase the technological knowledge available to the general public, which could encourage and stimulate further innovation (Seymore, 2010). Traditionally, patents function has accordingly been understood as disclosure of information in exchange for protection (Long 2002).

Act No. 9 of December 15, 1967 on patents (The Norwegian Patents Act) constitutes the legislative framework for patents in the Norwegian law. For an invention to be eligible for patenting, it has to provide a technical solution to a problem. The solution has to be new, represent an inventive step and show industrial applicability. One cannot be granted a patent without explaining or showing how the invention can be implemented in practice (NIPO, 2016; The Norwegian Patents Act, 1967). The protection is generally limited to a maximum of twenty years from the filing date. In the Norwegian system, you will receive a first assessment of the technology's patentability within 7 months, and the patent application is made publicly available 18 months after the filing date. It usually takes 1-2 years from when you receive the first assessment until the patent may be approved. If the patent is granted, the patent owner has to pay a yearly contingent to maintain their exclusive rights (NIPO, 2020a).

There are several different approaches to obtain a patent in Norway. The first possibility is to apply directly through the Norwegian Industrial Property Office (NIPO). It is also possible to apply through the Patent Corporation Treaty (PCT), where the applicant can apply to several countries simultaneously. PCT cannot grant a patent, but will forward the applications to the relevant national intellectual property offices, where decisions are made independently (NIPO, 2017). As of 2008, Norway is also a part of the European Patent Convention, where an applicant can apply through the European Patent Office (EPO) for patent rights in several member countries. The patent will be processed, and if eligible, approved centrally by the EPO (NIPO, 2020b).

In 2019 the NIPO received 752 patent applications from Norwegian companies. This represents a reduction by 12.8 percent from the number of applications in 2015, with the number declining almost every year (The Research Council of Norway, 2020). This could be due to more Norwegian applicants choosing to apply through the EPO, or fewer patents being forwarded from the PCT. The NIPO has however stated that the Norwegian applicants predominantly apply directly through the national system, but that the decline could be partially due to natural fluctuations (NIPO, 2019, 2020c). Yet, there are in general fewer patent applications and grants in Norway than in the neighbouring countries (WIPO, 2020).

In a report from 2019, The Research Council of Norway questioned the declining numbers. They argued that the number of applications should be higher, given that the workforce of Norway ostensibly becomes progressively more competent over time. They theorize that the reason might be that the companies preferred to protect their knowledge by secrecy rather than by patents. Further, they refer to a survey conducted by Statistics Norway (SSB), which revealed that of the Norwegian companies conducting innovative activities between 2016 and 2018, 27 percent chose trade secrets as their strategy, while only 7 percent applied for patents (The Research Council of Norway, 2019).

2.2 Financial constraints

2.2.1 Defining financial constraints

Financial constraints are not a directly observable firm characteristic, and it is therefore challenging to precisely define what financial constraints are and which firms that are financially constrained. As a general concept financial constraint can however be defined as frictions that prevent firms from conducting all desired investments due to lack of financing availability or high costs of financing (Lamont, Polk, & Saaá-Requejo, 2001). These frictions can include several factors, but according to Tirole (2006, p. 238) mainly arise due to information asymmetries between the firm and external capital sources.

Tirole's description of financial constraints has roots in the pecking order theory of capital structure, introduced by Myers and Majluf (1984). The theory claims that firms prefer internal financing over external. The hierarchy is based on the capital costs associated with the different financing sources, due to information asymmetries and adverse selection. It is assumed that managers know more about the company than potential investors and that they act in the interest of existing shareholders.

The theory implies that if the manager acts in accordance with the assumptions, new equity can only be issued if it is not at a disadvantage for the existing shareholders. Consequently, if new stocks are issued it signals to potential investors that the manager considers the company stock to be overvalued. Anticipating this, the company may refrain from issuing new stocks, even for projects with a positive net present value. This creates an adverse selection problem for potential investors, which will raise the risk premium. According to the pecking order theory acquiring debt would offer a lower capital cost than equity, but higher than retained earnings, which means that acquiring any external capital will have an additional cost to internal capital. This will lead to a "wedge" between the capital cost of internal and external capital. The size of the wedge represents the magnitude of the financial constraints the firm faces.

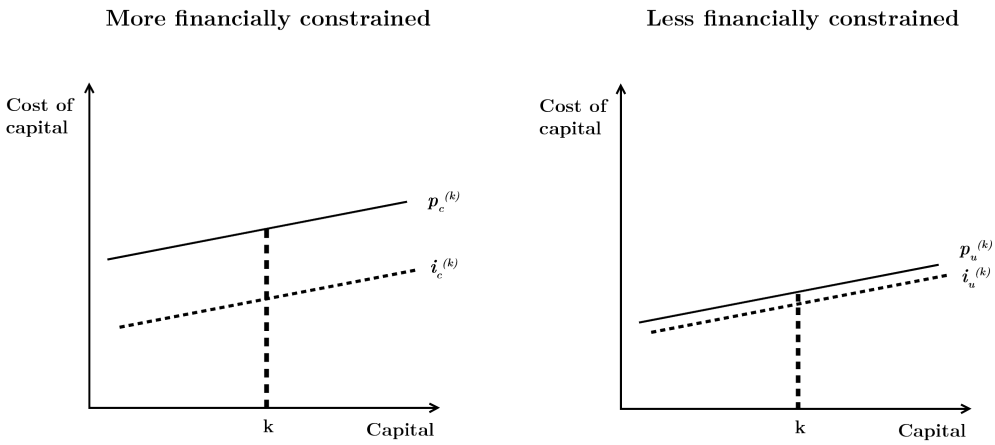

Figure 2.1: Wedge between internal and external cost of capital

Notes: The graph to the left shows the “wedge” in internal and external cost of capital for a more financially constrained firm. The ${e_c}^{(k)}$-line symbolizes the cost of external capital the ${i_c}^{(k)}$-line symbolizes the cost of internal capital. The graph on the right shows the same for a less constrained firm (Farre-Mensa & Ljungqvist, 2016)

2.2.2 Measuring financial constraints

Empirically identifying the presence and magnitude of financial constraints on a firm-level has proven to be problematic. This has led to several different approaches and extensive debate among researchers on the validity of the different approaches. As noted by Carreira and Silva (2012), it is hard to pinpoint a superior approach as each method comes with advantages and disadvantages.

One of the earliest and most influential approaches to measuring financial constraints are investment cashflow sensitivity models. In their seminal paper on the topic, Fazzari, Hubbard and Petersen (1988) propose a method for measuring and comparing the degree of financial constraints a firm is subject to. The approach builds on the q-theory of investment suggested by Tobin (1969). The q-theory argues that a value maximising firm will continue to invest in physical capital as long as the marginal replacement value of the existing physical capital is lower than the market value of the firm. Fazzari et al. (1988) substituted the unobservable marginal Tobin’s q for average Tobin’s q, following Hayashi (1982), and added cash flow to adjust for market imperfections. The degree of investment sensitivity to cash flow would consequently function as a measure of the financial constraints a firm is facing in an imperfect market.

The model of Fazzari et al. (1988) is exhibited in equation 2.1.

$$(\frac{I}{K})_{i,t} = \beta_1 + \beta_2 q_{i,t} + \beta_3(\frac{CF}{K})_{i,t} + \beta_4(\frac{CF}{K})_{i,t-1} + u_{i,t} \tag{2.1}$$

Where $\frac{I}{K}$ is the investment to physical capital ratio, q is average Tobin's q which controls for the firm's investment opportunities and $\frac{CF}{K}$ is the cashflow to physical capital ratio.

Fazzari et al. (1988) verified the model by studying American manufacturing firms' investment sensitivity to cashflow. Using a comparative approach, they found a stronger correlation between investment and cashflow for the firms they deemed more likely to be financially constrained. They created four subsets based on the firms' dividend pay-out behaviour. The rationale for subsetting the companies based on dividend pay-outs was that if firms were financially constrained, having a large "wedge" between external and internal capital, they would be withholding dividends to increase internal capital.

The cashflow sensitivity approach of defining financial constraints has in later studies been employed and adapted to several different countries and contexts, as well as used with various splitting criteria. It has become the most common way to define financial constraints (Carreira & Silva, 2010). However, one of the major drawbacks of the model is that one has to have access to accurate market valuations of the firms' capital to compute average Tobin's q. Using the method on firms that are not listed on the stock exchange therefore requires adjustment and other control variables. Himmelberg and Petersen (1994) use sales growth to catch some of the same effects as Tobin's q, an approach adopted in several following papers.

The cashflow sensitivity method has also received criticism on several of its key aspects and assumptions. Kaplan and Zingales (1997) remarked on how the curvature of the external capital cost line is unknown. They also questioned the dividend pay-out splitting criteria used by Fazzari et al. (1988). The validity of substituting marginal Tobin's q for average Tobin's q has also been discussed. In the case that the average Tobin's q does not fully reflect the investment opportunities of the firm, cashflow itself might reveal additional information about the firm and capture this in the model. Alti (2003) found that in a financially frictionless model, after fully correcting for firms' q, the results still showed significant investment cashflow sensitivity. This indicates that Tobin's q cannot fully capture a firm's investment opportunities.

2.2.3 Measuring patents effect on financial constraints

Hottenrott et al. (2016) builds on the investment cashflow sensitivity model proposed by Fazzari et al. (1988) and subsequent models investigating the relationship between cashflow sensitivities and R&D. In their model cashflow is substituted by another internal capital measure: working capital. To measure the influence of patenting they include a variable of the accumulated stock of patent applications depreciated by 15 percent yearly. Further, they implement an interaction term between the patent variable and working capital. By using a Tobit Random effect model, they investigate if the presence of former patenting activity can help companies alleviate their dependency on internal capital. The model is exhibited in equation 2.2.

$$(\frac{R\&D}{K})_{i,t} = \beta_1 + \beta_2 ln(PATSTOCK)_{i,t-1} + \beta_3(\frac{WCAP}{K})_{i,t-1} + \beta_4(\frac{WCAP}{K})_{i,t-1}$$
$$\times ln(PATSTOCK)_{i,t-1} + \beta_5(\frac{Debt_{i,t-2}}{K_{i,t-1}}) + \beta_6 ln(K)_{i,t-1} + \sum_{h=5}^{8} \beta_h Zi,k + \gamma_i + \delta_t + \alpha_i + u_{i,t} \tag{2.2}$$

Where $\frac{R\&D}{K}$ is the research and development investments to beginning of year physical capital ratio. $ln(PATSTOCK)$ is the logarithm of the variable depicting former patenting activity. $\frac{WCAP}{K}$ is the working capital to physical capital ratio. $\frac{Debt}{K}$ is the long term debt to physical capital ratio and $ln(K)$ is the logarithm of physical capital. $Z_{i,k}$ is firm level control variables. γ_i is the industry code dummies and δ_t is the represents time dummies.

The rationale behind using working capital instead of cashflow is based on Hall and Kruiniker (1995). They argue that working capital better reflects the funds available to the firm to make new investments. By retaining cash earnings, firms accumulate the financial funds necessary to conduct investments. As opposed to cashflow, working capital also includes values that can be converted into cash relatively easily. Therefore, it can be used by firms to smooth investments in R&D and physical capital. Working capital can consequently be seen as a stock of liquid assets rather than the flow of liquidity in the firm.

As Hottenrott et al. (2016) is inspired by the investments cashflow sensitivity model some of the associated criticism will be applicable to their model as well. For instance, the critique related to the use of splitting criteria for segmenting the firms into different subsets, with assumed differences in the degree of financial constraints. To do this one has to define cut-off points. If the relationship between financial constraints and the method of division is non-monotonic, the placement of the cut-off points may influence the results. Additionally, the firms can move across the segmenting variable during the sample period. This can lead to challenges in creating suitable segmenting criteria (Silva & Carreira, 2012).

2.3 Financial constraints in R&D active firms

Although asymmetric information and financial constraints could be a problem for any firm, there are some characteristics of firms engaging in R&D activities that potentially lead to an increased likelihood for financial constraints. Firstly, R&D projects are characterized by large and usually firm-specific investments with low collateral value (Hottenrott et al., 2016). Furthermore, valuating R&D-projects is challenging. Current asset pricing approaches are likely to fail due to the difficulties of capturing the uncertain expected future revenue of R&D activities (Scellato, 2007). Obtaining credible information about R&D-projects might therefore present a substantial acquisition cost. This can make it both costly and challenging for outsiders to judge R&D-performing firms' quality.

R&D-performing firms who seek financing will also have an incentive to exaggerate the positive quality of a project to potential investors and lenders, which further exacerbates the information asymmetry between the firm and potential investors and lenders. This has several implications in the market for external financing. The mechanisms of asymmetric information in equity financing are a well-known problem in corporate finance. As explained by the pecking order theory, investors will believe that managers act in the best interest of pre-existing shareholders and therefore only issue equity if they get a price that overvalues the firm (Tirole, 2006).

Although this kind of problem is mostly discussed for the equity financing part of external capital, the asymmetric information between a lender and the firm might affect debt financing as well. Without accurate information about the quality of the firm's R&D, lenders might choose not to lend at all or for the risk premium to reflect average project quality in the market. The latter can result in a "lemons premium" for firms with above-average projects (Leland & Pyle, 1977). There are also challenges related to collateral. Banks and other lenders will commonly require some sort of collateral before being willing to grant a loan. As mentioned, R&D investments are however generally associated with a low collateral value (Czarnitzki & Hottenrott, 2011; Scellato, 2007). Overall, this could make it challenging to obtain loans for R&D-active companies.

The challenges related to financial constraints may be especially severe for small and young R&D-active firms. A smaller portion of these firms have publicly traded securities, and their activities are less likely to be publicly available or reported in the press. This could lead to an increased cost of information (Berger & Udell, 1998; Hottenrott et al., 2016). Furthermore, small and young R&D active firms will typically have less physical capital that could be applicable as collateral to back loans. It is also likely that small companies in general request smaller loans than larger firms, increasing the lender's relative cost of obtaining information (Hottenrott et al., 2016). Additionally, young firms are dependent on establishing a new relationship with the financial institution. In other words, they are unable to rely on advantages associated with established relationships, that could have been used to reduce information asymmetries and moral hazard problems (Berger & Udell, 2002).

In summary, since the cost of external capital is expected to be higher for R&D-active firms, financially constrained firms engaging in R&D are more likely to rely on retained earnings to finance their activities (Czarnitzki & Hottenrott, 2011; R. Hall, 1992) This will, in turn, restrict R&D efforts in firms with limited access to internal financing and with potential R&D projects in need of financing. This could lead to otherwise worthwhile projects being delayed, cancelled or postponed.

2.4 The role of patents in alleviating information asymmetries

In accordance with section 2.3 firms engaging in R&D-projects may be subject to financial constraints. Patents could however represent a valuable contribution in mitigating the information asymmetry, as discussed in Long (2002). She transcends the “simple view” of patents as merely an exchange of public disclosure for legal protection and argued that patents also are an instrument to convey information about the underlying innovation or the patentee. Hottenrott et al. (2016) divide this effect into two groups.

The first rationale is that patents offer the patentee a credible way to convey information about the invention to potential lenders or investors. Patents, as well as patent applications, are required to include a detailed description of the invention and a patent claim, where the scope of the patent is defined and specified. Patents thus include valuable and verifiable information for potential lenders and inventors at a relatively low acquisition cost (Long, 2002). This implicates that also patent applications, which have not yet been granted or denied, may have a value as they allow external parties to evaluate the particular technology (Harhoff, 2009).

If the patent is granted, a patent office has confirmed that the subject matter fulfils the requirements of a patentable invention. This entails that the invention has been through a certification process, and a third-party has verified that the invention is new, represents an inventive step to prior art and is suited for industrial use (Long, 2002). Even if the patent is not yet granted or denied, in the Norwegian system it will within seven months have been subject to a preliminary assessment of patentability (NIPO, 2020a). It should however be noted that the assessment and grant given by a patent office is not necessarily infallible and the true threshold to obtain a patent is a controversial topic (Hottenrott et al., 2016).

Second, if market actors believe that patents are correlated with firm attributes that are difficult to observe or measure, patents may work as a signal of those qualities (Hottenrott et al., 2016). If a lender or investor assumes that companies with patents are more likely to have higher productivity, R&D success or future value, the patent can work as a means of conveying information about those attributes to the intended recipients (Long, 2002). The signal thereby helps outsiders derive expectations about properties that cannot be immediately observed. Patents may therefore have a valuable signalling effect that can mitigate the information asymmetry between the patentee and potential lenders, or investors (Hottenrott et al., 2016).

Several studies have shown that a relationship between patents and desirable firm attributes does exist. A study conducted by Helmers and Rogers (2011) found that firms owning a patent had a larger growth rate, while Hall, Helmers, Juster and Sena (2013) suggest that there is a positive association between patents and innovative performance. Various studies have also shown a positive correlation between R&D expenditure, patent stocks and market value (Czarnitzki, Hall, & Oriani, 2006; B. Hall, 1999; B. Hall, Jaffe, & Trajtenberg, 2005). This might lead to lenders or inventors extrapolating the future value of a firm based on their patenting activity (Hottenrott et al., 2016). For a lender, an especially important property may be the probability of a potential debtor going bankrupt. Both Cockburn and Wagner (2010) and Mann and Sager (2007) found that owning patents was positively correlated with the survival of the firms.

2.5 Empirical evidence

A number of studies have detected a positive relationship between patenting activity in start-up companies and early-stage financing. Baum and Silverman (2004) found a positive correlation between patent applications at the US Patent Office (USPTO) and venture capital (VC) financing, but noted that the effect varies across industries. Interestingly, they also observe that the effect of patent grants is smaller than the effect of patent applications. On a sample of German and British biotechnology companies, Haeussler, Harhoff and Mueller (2009) found that having submitted at least one patent application reduced the time to receive a venture capital investment by 76 percent.

Mann and Sager (2007) researched the relation between patenting activity in software start-ups and VC availability. They discovered a positive correlation between patenting and several success measures, such as the number of financing rounds, total investments, the ability of the firm to exit the venture capital cycle successfully, acquisition of late-stage financing, and as mentioned longevity. They also observed that the size of the patent portfolio mattered less than having at least one measure of patenting activity. Hsu and Ziedonis (2013) studied 370 venture-backed semiconductor start-ups and finds that patents have the ability to signal quality to potential investors. This applies especially in the early stages of financing when the patentee lacks credible means of conveying information about the quality of the firm's technology.

In the case of later-stage financing, there are fewer studies to rely on and the findings are indefinite. Deeds, Dona and Coombs (1997) found no effect of patents in the capital raised in the firm's initial public offering (IPO) within biotechnology start-ups. Heeley, Matuski and Jain (2009) found that patents only had an effect on the amounts raised in IPOs in certain industries, based on how transparent the link between patents and inventive returns are. They did for instance find evidence of a patenting effect in pharmaceuticals, but not within information technology firms. The study of Hottenrott et al. (2016) did as mentioned, look at the effect of patents on financial constraints in the Flanders. The study found that patenting activity alleviates financial constraints in smaller firms, but not in bigger companies. They attribute this to smaller firms being more reliant on external financing. Additionally, they split the sample into companies over and under 25 years old. The results showed no significant effect of financial constraints in either of the subsets.

3 Hypotheses

Following the theoretical background as well as the research question, we have developed a main hypothesis, supplemented by two subhypotheses. Firstly, patents and patent applications have attributes that may make them a useful instrument to credibly convey or signal information about the patentee or the underlying innovation to potential lenders or investors. This implies that it could work as a tool to mitigate information asymmetries, and by that lead to a reduced cost of external capital. With background in this reasoning, the first and main hypothesis is:

H1: Companies with a higher degree of prior patenting activity will be subject to less financial constraints, compared to firms with less prior patenting activity.

Furthermore, the effect of patenting activity may vary with particular company attributes or properties. Literature suggests that for small and young companies, the information asymmetries between the company and potential lenders or investors may be especially severe. Consequently, the cost of obtaining external capital rises and they become more prone to financial constraints, compared to larger and older firms. For the younger and smaller companies, acquiring tools to credibly convey information could therefore be of particular significance. Supplementary to hypothesis one, we therefore present hypothesis two and three:

H2: Patenting activity will have a greater influence on financial constraints in smaller companies, compared to larger companies.

H3: Patenting activity will have a greater influence on financial constraints in younger companies, compared to more established companies.

4 Data

In this section, we present and describe the data used in our research. First, we give an introduction to our main data sources: patent data from the Norwegian Industrial Property Office, and company information and accounting data retrieved from a database constructed by NHH's Centre for Applied Research. Next, we describe the construction of variables and subsets, as well as how the dataset was processed and cleaned. Last, we will present our final dataset through summary statistics.

4.1 Data sources

4.1.1 The Norwegian Industrial Property Office

The Norwegian Industrial Property Office (NIPO) provides data on publicly available patent applications from Norwegian applicants to NIPO or PCT. EPO applications are not included. The patent applications were matched up with organisation numbers as the product of a collaborative project with Statistics Norway (SSB) and the Nordic Institute for Studies in innovation, research and education (NIFU). From 2007 the NIPO maintain a consistent match between patent applications and Norwegian organisation numbers. The current analysis is therefore based on data from 2007-2018.

4.1.2 Database of accounting and company information from NHH's Centre for Applied Research

The database constructed by NHH's Center for Applied Research (from now on denoted as "The SNF database") consists of accounting and company information for all Norwegian enterprises and groups in the time period 1992-2018. The data is mainly sourced from the Brønnøysund Register Centre via Bisnode D&B Norway (Berner, Mjøs, & Olving, 2016). The database includes two main categories of datasets: accounting data and company data, which are further divided into one dataset for each year. In this paper, we apply data from both categories in the years 2007-2018.

4.2 Construction of variables

In the following section, we will describe how the variables used in the analysis are constructed. The main variables of interest are investment, patenting activity and internal liquidity. Further, there are two additional control variables: debt and physical capital stock.

4.2.1 Dependent variable

We use physical investments (I) as our dependent variable. The variable is constructed as the change in total physical capital from one period to the next. It is adjusted for the depreciation of assets [1]. The composition is displayed in the following equation: $Investment(I)_{i,t-1} = Physical\ Capital(K)_{i,t} - (Physical\ Capital(K)_{i,t-1} - Depreciation_{i,t-1})$

The variable is based on physical investments, instead of R&D investments, due to the lack of data on R&D spending. It is challenging to obtain non-anonymized firm-level data on R&D expenditure. The approach of using physical investments is however not unprecedented. Similar methods are for instance seen in Scellato (2007). Himmelberg and Petersen (1994) reasoned that financing of physical investments for R&D-intensive firms would be more prone to moral hazard and adverse selection problems. They elaborated upon this by arguing that it would be inappropriate to view the firm as having access to separate sources of finance for R&D and physical investments. Furthermore, based on Schumpeter (1942) they reasoned that new knowledge must to some extent be embodied in physical investments.

As our sample consists of a broad spectrum of firms, and not solely on companies specializing exclusively in R&D, we expect this to hold true for many of the included companies. Physical capital also has the advantage of strict and uniform accounting practices and ease of valuation. We therefore believe physical investments are a robust measure of investment activity. Consequently, we argue that physical investments' sensitivity to internal liquidity is a relevant proxy for measuring the financial constraints the firms of our sample are subject to.

[1]Adjusting for the deprecation of assets gives us a slightly inflated investment measure. This is because the deprecation in the accounting data contains deprecation of both tangible and intangible assets. Analysing our dataset the size of this effect does however appear to be minor.

4.2.2 Internal capital

In several seminal studies where they measure financial constraints, cashflow was used as a measure of internal capital. By the rationale presented in section 2.2.3, we do instead choose to use the firm's stock of working capital ($WCAP$) as our measure of internal liquidity. The variable is based on the standard accounting definition of working capital. We therefore construct the variable by subtracting the firm's current liabilities from its current assets.

4.2.3 Patent application stock

The patent variable is based on publicly available patent applications, rather than granted patents. Building on the findings of Hauesler et al. (2009), Harhoff (2009) argues that the information that is relevant for an investor or debtor is not reserved to the grant event, and thus that the signalling value of patents is not contingent on the term that the patents are granted. Hottenrott et al. (2016) also build their analysis on this rationale, and have chosen to use patent applications as the foundation for the main patent variable. To include the full potential effect of patenting activity in the analysis we have therefore chosen to use publicly available patent applications as the basis of the $PATSTOCK$-variable.

Further, the variable is computed as a depreciated cumulative sum of a company's past patent applications. By depreciating the sum we place an emphasis on the most recent patenting activity, while still capturing the impact of the patent application stock from earlier years. The variable is defined as: $PATSTOCK = (1 - \delta)PATSTOCK_{i,t-1} + Patent\ Applications_{i,t}$, where δ is a constant depreciation rate of 15 percent. The choice of this depreciation rate follows the example of Griliches and Mairesse (1984, pp 339-374).

4.2.4 Control variables

In addition to our main variables of interest, we also include control variables. In the foundational models identifying financial constraints using investments cashflow sensitivity, Tobin's q was used as a sole control for the future investment propensity. It was believed that the variable summarized all relevant information (Chirinko, 1993; Fazzari et al., 1988). However, it has later been shown that this assumption is problematic (Alti, 2003; Blundell, Bond, Devereux, & Schiantarelli, 1992). Further, the construction of an average Tobin's q requires accurate market valuations of the companies. As only 17 of the companies in the sample are listed on the stock exchange, we cannot compute Tobin's q for our dataset. We therefore need to rely on other controls to capture the effect of firms' future investment propensity.

We use the beginning-of-year debt ($DEBT_{t-1}$) as a measure of a firm's balance situation and its access to the debt market (Hart & Moore, 1995). Debt is defined as all long-term liabilities expiring in more than a year. We also include beginning-of-year physical capital (K_{t-1}) in order to control for possible scalar effects related to the size of the companies.

4.2.5 Lagging and deflating of variables

The accounting variables I, $WCAP$ and $DEBT_{t-1}$ are deflated using K_{t-1}. This is done to reduce problems with heteroscedasticity in the sample (Fazzari et al., 1988). To address the concern of simultaneity between our independent and explanatory variables we lag all time-varying explanatory variables by one year. As debt and physical capital is already lagged once to get beginning-of-year values, this entails that they will be lagged twice[2]. The issues of heteroscedasticity and simultaneity will be elaborated upon in section 5.

$PATSTOCK$ is also lagged by one year. This is done to ensure that the effect of the patenting activity occurs before the potential physical investment, as the patent application could be filed at any time during the year.

4.3 Data preparation

4.3.1 Data merging

To conduct the analysis, we constructed a panel dataset using R Studio 1.3.1093 and Stata 16.0. The company and accounting data were merged based on their organisation number and year. To be able to implement the patent application data, we created a data frame summarizing the number of patents the individual companies applied for

[2]The use of lagged variables shortens the time span of the analysis by two years. We are thereby using data from 2007-2018 to investigate the time period 2009-2018.

each year in the relevant time period. This data frame was further merged with the accounting and company information based on their organisation number and accounting year. All included companies have at least one patent application over the sample period. This resulted in a dataset with 17 383 observations, 5599 patent applications and 2000 companies.

From the original patent dataset, 1565 patent applications were not matched with the data from SNF. 1409 of these were applied for without an organisation number. The remaining 156 patent applications seem to mainly be from companies that are not subject to accounting obligation, such as firms organised as a sole proprietorship or as an organisational section. Furthermore, 50 of the organisations that were included in the dataset had a cumulative sum of zero patent applications over the chosen time period. The problem seemed to arise for companies that applied for a patent within the chosen time period but did not have available accounting data in the same years as they applied for the patent. We chose to delete the relevant observations.

4.3.2 Data cleaning

The accounting data from the SNF database exhibit certain inconsistencies and unrealistic observations. Additionally, not all companies in the database are relevant or applicable to our research. It is therefore necessary to establish some conditions for the observations and companies that are to be included in the analysis. First, companies have to make at least one physical investment in the 10-year sampling period to be included in the dataset. If they do not make any investments, they will not have any effect on the analysis and are therefore redundant. Companies that have no revenue are also removed as they appear to be inactive, making them less relevant for the analysis. This is in accordance with the reasoning seen in the quality assurance of the database (Berner et al., 2016).

Furthermore, the observations cannot exhibit negative sales revenue, total assets or debt values, since these variables exhibiting negative values would be illogical in practice. Note that debt is presented as positive values in the database, so a negative debt value would indicate positive debt, i.e., debt less than zero. The occurrence of illogical observations might be due to errors in the database or varying accounting practices or strategies.

We also remove companies with observations of zero physical capital. Our method is dependent on using tangible assets as a deflator for other variables and it is therefore not viable to include companies with zero physical capital. Last, each company needs to be observed at least three times in the SNF database over the relevant time period. This is due to two reasons. The first is that our panel data model controls for unobserved heterogeneity, and we do thus require more than one observation. The second reason is that the applied method requires lagging of selected variables. Certain variables are even lagged twice, which leads to the specific condition of three observations.

After eliminating the data that does not meet the established conditions, as well as missing values in the relevant variables, our final data sample consists of 8191 observations, 1224 companies and 2923 patent applications. How many observations that were removed in each step of the cleaning process is exhibited in appendix A1.

4.3.3 Outliers

When examining our dataset with the constructed variables, we discovered there were several outliers. There are two main reasons to this. First, even after cleaning the data, a few singular observations exhibited unreasonable values. This is probably due to errors in the SNF database.

Moreover, the creation of ratio variables leads to a portion of extreme values. We for instance observe that this happens to the investment variable for certain companies with peculiarly small physical capital stocks. Some investments in physical capital, that arguably are not large, will obtain a large investment ratio value if the original physical capital stock is extremely small. The consequence is that the methodology is a source of extreme outliers. In order to minimize the influence of the extreme values, we winsorized the ratio variables at a 90 percent level. This entails that observations larger than the 95^{th} percentile are set to the value of the 95^{th} percentile, and the observations smaller than the 5^{th} percentile are set to the value of the 5^{th} percentile. We choose to do this instead of trimming the data, as we believe that the observed growth to some extent is valid. However, if not winsorized the observations would have an unreasonably large influence due to the use of ratios.

4.4 Construction of subsets

4.4.1 Size classifications

To investigate hypothesis two, we classify the companies based on their size. There are three different categories: small, medium, large. The class for each company is based on their size in the last year they appear in the dataset. The conditions to fall within each of the categories are based on the classifications created by Orbis Global Database from Bureau van Dijk. The Orbis database originally has four categories, including "very large". However, since only approximately 28.5 percent of the dataset falls within the "very large" or "large" classification, we have chosen to combine these categories.

To be classified as "large" the company has to fulfil at least one of the following conditions:

- Operating revenue has to be larger or equal to 10 million EUR.
- Total assets have to be larger or equal to 20 million EUR.
- The number of employees has to be larger or equal to 150.

To be classified as "medium" the company has to fulfil at least one of the following conditions:

- Operating revenue has to be larger or equal to 1 million EUR.
- Total assets have to be larger or equal to 2 million EUR.
- The number of employees has to be larger or equal to 15.

If the company is not included within one of the mentioned categories it will be classified as "small" (Orbis, n.d.). A simplified conversion rate of 10 NOK per 1 EUR has been applied. How the sample is distributed between the size subsets is exhibited in table 4.1.

Table 4.1: Distribution of size categories

	Nr. of observations	Percentage	Nr. of companies
Small	2,303	28.1 %	449
Medium	3,504	42.8 %	487
Large	2,343	28.6 %	279
NA	41	0.5 %	9
Sum	8,191	100%	1,224

4.4.2 Age classifications

To investigate hypothesis three, we create an AGE-variable. The variable is calculated by extracting the year of establishment from the year of the observation. We classify the companies that are older than 10 years as established, and the companies with age less than or equal to 10 years are classified as young. Since the companies are divided by the age in each observation, they can change category during the time span of the sample period. The same company can thus be categorized first as young and later as established. The distribution of observations in the age subsets is presented in table 4.2.

Table 4.2: Distribution of age categories

	Nr. of observations	Percentage	Nr. of companies
Age $<=$ 10	2,941	35.9 %	733
Age $>$ 10	5,250	64.1 %	812
Sum	8,191	100%	

4.5 Descriptive statistics

4.5.1 Descriptive statistics of relevant variables

Table 4.3 exhibits descriptive statistics for relevant variables in the full sample. The companies are on average 18.03 years old, with 158.4 employees. The median for employees is however only 19, indicating that half of the observations are of companies with 19 or fewer employees. On average the companies apply for 0.36 patents every year and hold a depreciated patent application stock of 1.66.

Table 4.3: Descriptive statistics full sample

Full sample: 8191 observations, 1224 companies						
Variable	**Units**	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**
Age	years	18.03	14.00	14.99	2.00	113.00
Employees	people	158.40	19.00	799.61	0.00	20,179.00
Patent applications	count	0.36	0.00	1.41	0.00	31.00
$I_{i,t}/K_{i,t-1}$	ratio	0.87	0.23	1.62	-0.05	6.63
$K_{i,t-2}$	thousand NOK	573,519.00	2,767.00	9,053,337.00	1.00	270,864,000.00
$PATSTOCK_{i,t-1}$	count	1.66	0.72	5.32	0.00	101.98
$WCAP_{i,t-1}/K_{i,t-2}$	ratio	11.32	1.79	24.44	-8.86	95.23
$DEBT_{i,t-1}/K_{i,t-2}$	ratio	4.03	0.68	8.64	0.00	35.54

Table 4.4 displays descriptive statistics divided into the size subsets. Naturally, age and physical capital are on average higher for the larger companies, compared to the smaller companies. The larger companies do also on average have a higher amount of patent applications per year and a larger depreciated patent application stock. These variables appear to increase gradually with each size subset. The maximum and minimum values for several of the ratio variables are equal for all subsets due to winsorizing.

Table 4.4: Descriptive statistics size subsets

Small companies: 2303 observations, 449 companies						
Variable	**Units**	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**
Age	years	12.17	10.00	8.29	2.00	54.00
Employees	people	4.93	3.00	5.55	0.00	74.00
Patent applications	count	0.17	0.00	0.45	0.00	5.00
$I_{i,t}/K_{i,t-1}$	ratio	0.85	0.08	1.73	-0.05	6.63
$K_{i,t-2}$	thousand NOK	1,328.00	312.00	2,948.40	1.00	42,641.00
$PATSTOCK_{i,t-1}$	count	0.78	0.61	0.41	0.00	13.55
$WCAP_{i,t-1}/K_{i,t-2}$	ratio	11.42	1.65	24.36	-8.86	95.23
$DEBT_{i,t-1}/K_{i,t-2}$	ratio	3.65	0.39	8.33	0.00	35.54
Medium companies: 3504 observations, 487 companies						
Variable	**Units**	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**
Age	years	16.90	13.00	13.55	2.00	100.00
Employees	people	29.85	21.00	31.08	0.00	255.00
Patent applications	count	0.23	0.00	0.64	0.00	15.00
$I_{i,t}/K_{i,t-1}$	ratio	1.01	0.29	1.73	-0.05	6.63
$K_{i,t-2}$	thousand NOK	8,192.00	2,518.00	16,088.52	1.00	253,355.00
$PATSTOCK_{i,t-1}$	count	1.04	0.70	0.50	0.00	25.46
$WCAP_{i,t-1}/K_{i,t-2}$	ratio	13.37	2.86	25.76	-8.86	95.23
$DEBT_{i,t-1}/K_{i,t-2}$	ratio	3.63	0.70	7.89	0.00	35.54
Large companies: 2343 observations, 279 companies						
Variable	**Units**	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**
Age	years	25.65	22.00	18.66	2.00	113.00
Employees	people	502.00	159.00	1,435.72	0.00	20,179.00
Patent applications	count	0.73	0.00	2.43	0.00	31.00
$I_{i,t}/K_{i,t-1}$	ratio	0.67	0.25	1.26	-0.05	6.63
$K_{i,t-2}$	thousand NOK	1,991,365.00	60,791.00	16,846,598.00	1.00	270,864,000.00
$PATSTOCK_{i,t-1}$	count	3.44	0.85	0.89	0.00	101.98
$WCAP_{i,t-1}/K_{i,t-2}$	ratio	8.20	0.82	22.09	-8.86	95.23
$DEBT_{i,t-1}/K_{i,t-2}$	ratio	4.91	0.84	9.79	0.00	35.54

Table 4.5 shows descriptive statistics divided into the age subsets. Contrary to what one would expect, the younger companies exhibit a higher physical capital mean than the established companies. When examining the data we found that this is due to a subsidiary of Equinor established during the sample period, which has a large influence on the average value. If we exclude this subsidiary the average physical capital stock for young companies is 59 061 thousand NOK. The younger companies do on average have a smaller depreciated patent application stock, but the average number of patent applications every year is only slightly smaller.

Table 4.5: Descriptive statistics age subsets

Young companies: 2941 observations, 733 companies						
Variable	**Units**	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**
Age	years	6.44	7.00	2.40	2.00	10.00
Employees	people	50.02	9.00	270.30	0.00	5,540.00
Patent applications	count	0.33	0.00	1.18	0.00	30.00
$I_{i,t}/K_{i,t-1}$	ratio	1.06	0.27	1.82	-0.05	6.63
$K_{i,t-2}$	thousand NOK	791,501.00	978.00	13,322,243.00	1.00	270,864,000.00
$PATSTOCK_{i,t-1}$	count	0.53	0.54	0.55	0.00	67.05
$WCAP_{i,t-1}/K_{i,t-2}$	ratio	12.19	1.72	25.90	-8.86	95.23
$DEBT_{i,t-1}/K_{i,t-2}$	ratio	4.27	0.65	9.06	0.00	35.54
Established companies: 5250 observations, 812 companies						
Variable	**Units**	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**
Age	years	24.52	20.00	15.17	11.00	113.00
Employees	people	218.70	31.00	971.96	0.00	20,179.00
Patent applications	count	0.37	0.00	1.52	0.00	31.00
$I_{i,t}/K_{i,t-1}$	ratio	0.76	0.22	1.48	-0.05	6.63
$K_{i,t-2}$	thousand NOK	451,407.00	5,356.00	5,332,543.00	1.00	262,675,058.00
$PATSTOCK_{i,t-1}$	count	1.87	0.64	0.68	0.00	101.98
$WCAP_{i,t-1}/K_{i,t-2}$	ratio	10.84	1.82	23.56	-8.86	95.23
$DEBT_{i,t-1}/K_{i,t-2}$	ratio	3.89	0.69	8.39	0.00	35.54

4.5.2 Distribution of observations

Figure 4.1 shows that there are approximately the same number of observations, and thus also companies, in the dataset each year. There is an average of 819 observations per year. Plot 4.2 reveals that the number of patent applications per year in the dataset is also relatively stable over the 10-year period. It is highest in 2009 with 320 applications and lowest in 2011 with 261 applications. The average number of patent applications per year is 292.

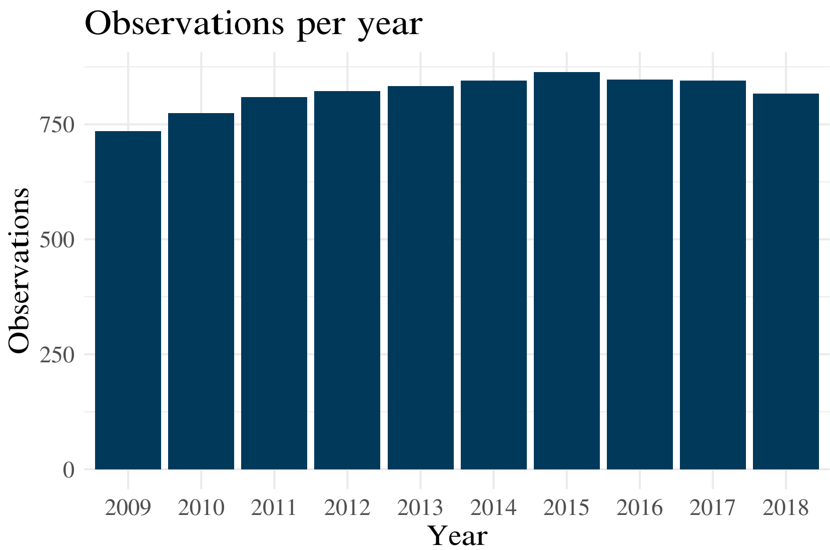

Figure 4.1: Number of observations per year

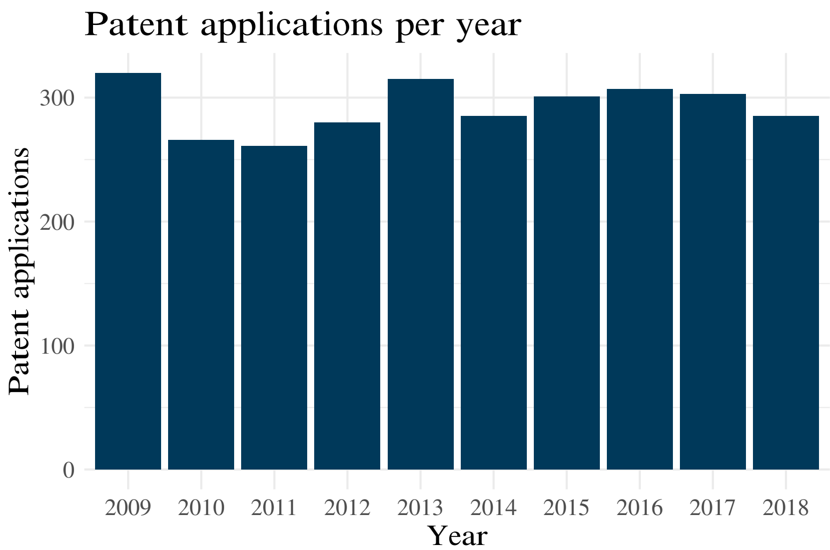

Figure 4.2: Number of patent applications per year

In plot 4.3 we see that most of the companies have data for the entire period of 10 years. There are however some companies where there only has been accounting data available for a portion of the years. This is likely because the company has become subject to account obligations during the period, or the company has gone out of business during the period, for instance due to bankruptcy. There are also companies where individual observations are removed, as they have not met the criteria specified in section 4.3.2.

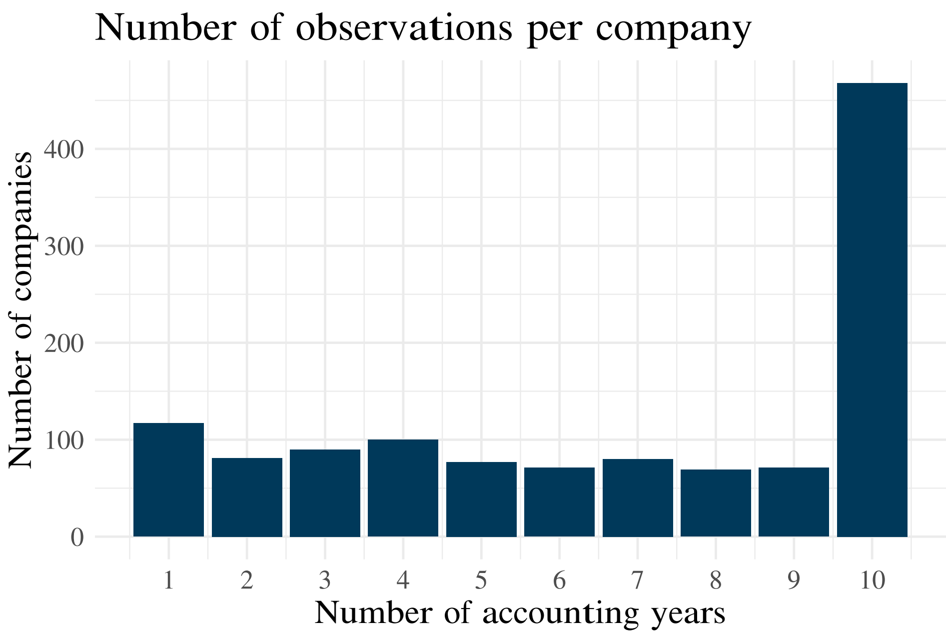

Figure 4.3: Number of observations per company

4.5.3 Sector distribution

In table 4.6 the distribution of observations divided into industry groups is exhibited. The industry groups are based on NACE codes. Specific information on which codes that are included in the different industry groups can be found in the quality assurance documentation paper accompanying the SNF database (Berner et al., 2016, p. 38). In our dataset, data from all industry groups are included. This means that the sample represents a broad variety of companies. However, companies classified as manufacturing firms or general services are overrepresented when compared to the entire dataset of SNF. Under the general services, companies classified as research companies are included. We have fewer observations of real estate and service companies, as well as trade and construction companies. These deviations from the SNF database are likely related to which industries where patenting is a prevalent strategy or Norwegian peculiarities. For instance, all Norwegian "borettslag" are categorised under the real estate and services industry group.

Table 4.6: Distribution of industry group

	Industry group	**Distribution of SNF database**	**Distribution of our data set**	**Difference**
1	Primary industries	1.71%	1.92%	0.21%
2	Oil/Gas/Mining	0.54%	3.69%	3.15%
3	Manufacturing industries	6.09%	29.10%	23.01%
4	Energy/Water/Sewage/Util.	0.86%	1.40%	0.54%
5	Building/Construction	11.20%	2.74%	-8.47%
6	Trade	18.77%	9.66%	-9.12%
7	Shipping	1.26%	0.70%	-0.56%
8	Transport/Tourism	5.76%	0.91%	-4.84%
9	Telecom/IT/Media	4.12%	5.95%	1.83%
10	Financce/Insurance	7.04%	1.58%	-5.46%
11	Real estate/Services	26.57%	2.87%	-23.69%
12	General Services	16.07%	39.48%	23.41%
		100.00%	100.00%	

5 Methodology

In this section, we will present the methodology of our analysis. First, we will introduce the objective and potential challenges. Next, qualities and assumptions associated with using a fixed effect model are discussed. Lastly, the model used in the current paper is presented and described.

5.1 Objective and potential challenges

The goal of this empirical analysis is to identify if it exists a causal link between former patenting activity and the degree of financial constraints a firm faces. More precisely, we want to see if former patenting activity reduces investment sensitivity to internal capital measured as working capital. We build the framework of our analysis around a method proposed by Hottenrott et al. (2016). We choose this methodology for identifying financial constraints and measuring patents' potential effect on said constraints, because it allows us to use a broad sample of Norwegian firms, not listed on stock exchanges. Hottenrott et al. (2016) use R&D investment data from the biannual OECD survey, merged with patent data and accounting data for firms in the Flanders. As mentioned earlier in the thesis, we do not have access to similar records for Norwegian firms, meaning that we need to modify the approach of Hottenrott et al.(2016) for it to be applicable to our data.

In the construction of the model, there is a risk of endogeneity, which could cause biased estimations (Wooldridge, 2013, pp. 86-88). A biased estimator is in expectation not equal to the parameter of interest, which is the true coefficient, meaning that the point estimates of the coefficients are systematically wrong in expectation.

To avoid endogeneity, we will be especially attentive to two factors. First, both working capital and investment in physical capital are most likely correlated with the unobservable future profitability of the firm. The unobservable future profitability of the firm is again linked to a large set of exogenous and endogenous variables. Implementing methods trying to mitigate the omitted variable bias caused by this and other factors will therefore be necessary. The second factor is the possible problem of simultaneity between our dependent variable, investments in physical capital, and the independent variables (Wooldridge, 2013, pp. 558-560). Feedback between these variables could lead to biases in our estimation, and must therefore be avoided.

5.2 Fixed effect

5.2.1 Fixed effect estimation

To address some of the issues regarding omitted variable bias, we choose to employ a fixed effect model on our data. As we have created a panel dataset, we can use panel data estimation techniques to better control for the unobserved firm-specific effect. One of the most widespread and used panel data estimation techniques is called within-group estimation, also known as a fixed effect estimation (Wooldridge, 2013, pp. 484-486). A fixed effect model will control for time-invariant unobservable characteristics specific to the firm. By time-demeaning all of the variables, all time-constant firm-specific effects are captured in the term $\alpha_{i,t}$. It is thereby removing potential biases in the model stemming from exogenous time-constant firm-specific effects. A fixed effect equation is exhibited in equation 5.1.

$$y_{i,t} = \beta_1 X_{i,t} + \alpha_i + u_{i,t} \tag{5.1}$$

Using the fixed effect model on an unbalanced panel dataset, like ours, is in principle unproblematic, but as noted in Wooldridge (2013, p. 491), issues can occur if the reason for the missing values i is correlated with the idiosyncratic error $u_{i,t}$, as this can cause a biased estimator. The reason for the missing i can however be correlated with the firm-specific effect $\alpha_{i,t}$.

One of the potential downsides of using a fixed effect model is that it excludes a lot of the variation in the data explained by variables fixed over the time period. For our analysis, this will be variables such as industry group, geographical location and age of companies. Even though age is not fixed for the companies over the time period, Wooldridge (2013, p. 488) notes that including variables that vary with the same amount for all groups over time has no effect in the fixed effect model.

By employing a fixed effect model, we can exclude exogeneity related to time-invariant firm-specific effects. This is important, as if we were not excluding the effect specific to the firm, we would expect our estimates to be biased. This is because the firm-specific unobserved effect, for example managerial abilities, is likely to be correlated with our variables of interest, like investment and patenting activity (Himmelberg Petersen, 1994).

5.2.2 Fixed effect assumptions

Three key assumptions for the fixed effect model are that the idiosyncratic error term $u_{i,t}$ should be uncorrelated with the explanatory variables in all periods, homoscedastic and serially uncorrelated. The errors are homoscedastic if the variance is constant over time and independent of the explained variable (Wooldridge, 2013, p. 51). They are serially uncorrelated if the errors in one period are uncorrelated with the errors in other periods (Wooldridge, 2013, p. 353). If these assumptions are violated, and not accounted for, the estimated coefficients of the model will be inefficient, but not biased (Wooldridge, 2013, p. 509). This means that the test statistics and significance levels produced by the model would be incorrect, since the correct standard errors are larger than what the model calculates without additional specification.

One common way in literature and econometric analysis to deal with heteroscedasticity and serial correlation is to use HAC-robust standard errors. This will adjust the downward biased standard errors and allow for some serial correlation and heteroscedasticity within groups. If possible, one would like to compute standard deviations and test statistics under the weakest set of assumptions possible.

Due nature of panel data, there can be heteroscedasticity present in the idiosyncratic error therms within firm. This can not be tested by traditional heteroscedasticity tests like the Breusch-Pagan test (Wooldridge, 2013, p. 277). We therefore deploy a modified Wald test for heteroscedastic error terms within firms(C. F. Baum, 2001). To test if the error term u_i is serially uncorrelated we will perform a Wooldridge test (Drukker, 2003). As we use a comparative approach with different subsets, we will need to perform the test for all subsets.

5.3 Model

5.3.1 Model specification

The model applied to the analysis is presented in equation 5.2. The components will be explained in the following segment.

$$\begin{aligned}\frac{I_{i,t}}{K_{i,t-1}} &= \beta_1 ln(PATSTOCK)_{i,t-1} + \beta_2 \frac{WCAP_{i,t-1}}{K_{i,t-2}} + \beta_3 \frac{WCAP_{i,t-1}}{K_{i,t-2}} \\ &\times ln(PATSTOCK)_{i,t-1} + \beta_4 \frac{Debt_{i,t-2}}{K_{i,t-2}} + \beta_5 ln(K)_{i,t-2} + \delta_t + \alpha_i + u_{i,t}\end{aligned} \tag{5.2}$$

5.3.2 Variables of interest and creation of an interaction term

As specified under section 4.2 the variables that are of interest to our analysis are: the dependent variable physical investment to physical capital stock-ratio ($I_{i,t}/K_{i,t-1}$), the explanatory variable working capital to physical capital stock-ratio ($WCAP_{i,t-1}/K_{i,t-2}$) and the depreciated patent application variable ($PATSTOCK_{i,t-1}$).

Following Hottenrott et al. (2016), we take the natural logarithm of ($PATSTOCK_{i,t-1}+1$) before applying it to the model. This is due to the large skewness in the distribution of patent applications. If the stock of patent applications is zero a logarithmical transformation would create missing values. To handle this we add one to all companies' patent application stock.

Additionally, we include an interaction term between ($WCAP_{i,t-1}/K_{i,t-2}$) and ($PATSTOCK_{i,t-1}$). This is done in order to explore if the presence of former patenting activity reduces the investment sensitivity to working capital. This variable and its coefficient (β_3) will be the key to answering our research question. It is important to note that by including an interaction term in our equation, we change the interpretation of the coefficients to the variables included in the interaction term.

5.3.3 Adding control variables

As mentioned, an important aspect in removing endogeneity from our model is to add theoretically sound control variables. The fixed effect model controls for firm-specific effects that are constant over time, such as industry group and origin region. In other words, we do not have to take such variables into account.

As specified in section 4.2.4 the first control variable is the ratio of debt to physical capital. This should capture the effect of the firms having high financial leverage and therefore having problems getting access to the external capital (Hart & Moore, 1995). Our second control variable is the physical capital, which is meant to control for firm size. This is included because the size of the firm might affect their ability to raise external capital or use economics of scale. As we expect the marginal effect of stock of physical capital to decrease we logarithmically transform the variable to better fit the data.

5.3.4 Time-fixed effect

We include year dummies to capture the effect of exogenous shocks. These are disruptions all or most firms are subject to, such as financial and macroeconomic shocks. Examples include a change in interest rates, taxes or economic downturns. The time dummies are added after the time demeaning of the model, meaning that the dummies have to be interpreted as the difference from the base year, in our case 2009. This is often referred to as a time-fixed effect, making our model a two-way fixed effect model with firm- and time-fixed effects.

5.3.5 Model assumptions

In addition to the fixed-effect assumptions, there are two supplementary assumptions associated with the model. First, the applied methodology for analysing patentings' effect on financial constraints is dependent on the assumption that financial constraints can be measured as the firm's sensitivity to working capital for physical capital investments. If this relationship does not hold true, the method will not be able to inform us about patents' effect on financial constraints.

The second assumption is that the relationship between patents' role in alleviating financial constraints and the segmenting variables used to divide our sample into subsets have a monotonic relationship. This entails that when one variable increases the other variable either strictly increases or strictly decreases (Clapham, 2001). If this assumption is violated, the placement of the cut-off points could potentially influence the outcome of our analysis.

6 Results

In the following chapter, we present the results of our empirical analysis. First, we describe how to interpret the coefficients associated with our model. Second, the results of the full sample are presented and described. Next, we examine the findings from the size subsets. This is followed by the findings from the age subsets as well as the results from subsets based on both age and size.

6.1 Interpreting the coefficients

Due to the use of semi-logarithmic functions, ratio variables, and an interaction term, interpreting the coefficients of the model involves several factors to be aware of. $PATSTOCK$ and K are logged variables regressed on a level-dependent variable. They must therefore be interpreted as follows: if the independent variable increase by one percent, the dependent variable changes by $\beta/100$. Further, the variables for working capital, debt and investment are measured as ratios. For the dependent variable, this means that the effect of the independent variables is measured as the effect on the investment/physical capital-ratio. $PATSTOCK$ and $WCAP$ are also integrated into an interaction term, they can therefore only be interpreted independently if one of the two are equal to zero.

6.2 Full sample

Table 6.1: Model estimates full sample

	(1) Default Std. errors	(2) HAC Std. errors
$lnPATSTOCK_{i,t-1}$	0.103**	0.103*
	(0.052)	(0.055)
$WCAP_{i,t-1}/K_{i,t-2}$	0.005***	0.005**
	(0.001)	(0.002)
$lnK_{i,t-2}$	-0.447***	-0.447***
	(0.020)	(0.034)
$DEBT_{i,t-2}/K_{i,t-2}$	0.014***	0.014***
	(0.003)	(0.005)
$WCAPi,t-1/K_{i,t-2} \times lnPATSTOCK_{i,t-1}$	-0.004***	-0.004
	(0.001)	(0.002)
Time-fixed effects included?	Yes	Yes
Modified Wald test	9.6e+36***	9.6e+36***
	0.0000	0.0000
Wooldridge test	151.81	151.81
	0.0000***	0.0000***
Observations	8191	8191
Adjusted R^2	-0.037	0.118

Modified Wald test is testing for heteroscedasticity in the idiosyncratic errors. Wooldridge test is testing for serial correlation in the idiosyncratic errors. * p<0.10, ** p<0.05, *** p<0.01

The first step of our analysis is to run tests for heteroscedasticity and serial correlation. We reject the null hypothesis for both the modified Wald test and the Wooldridge serial correlation test. This implies presence of heteroscedasticity and serial correlation in the idiosyncratic errors. The default standard errors can therefore not give us accurate test statistics and significance levels. We must consequently use HAC-robust standard errors.

As exhibited in table 6.1 the coefficients remain unchanged, but due to the increased standard errors, the significance levels are adjusted. We can for instance no longer point to a significant effect on a 5 percent level for the $PATSTOCK$-variable ($lnPATSTOCK_{i,t-1}$) or the interaction term. Due to identifying heteroskedasticity and serial correlation in the residuals for all subsets, the following regression tables will be reported with HAC-robust standard errors.

Following column two in table 6.1, we see that the working capital-variable ($WCAP_{i,t-1}/K_{i,t-2}$) is significant at a 5 percent level. This means that the working capital ratio of the prior year has a positive effect on the investment ratio in the current year. This indicates that the companies' investments are sensitive to the degree of internal liquidity, and thus that they are financially constrained. However, due to the interaction term, this effect can only be interpreted independently in situations where $PATSTOCK$ is equal to zero

The $PATSTOCK$-variable, exhibits a positive and weak significant effect at a 10 percent level. A one percent change in the stock of patent applications one period ago leads to an increase of 0,00103 (i.e., 0,01 $*\beta$) in the dependent variable $I_{i,t}/K_{i,t-1}$. This implies that an increase in the number of patent applications leads to an increase in investments. Yet, the variable must only be interpreted as an isolated effect in the case of zero working capital. The interaction term between working capital and patenting activity is close to significant on a 10 percent level with a p-value equal to 0.11. Due to the insufficient significance levels, we can however not draw any meaningful conclusions on the effect of patenting on financial constraints from these results. We do thus not find support for hypothesis one in the full sample with HAC-robust standard errors.

For the control variables, we detect the expected effects. A higher value in physical capital at the beginning of the prior period ($lnK_{i,t-2}$) shows a negative and significant effect on investments. Based on the assumption that a larger amount of physical capital two periods ago is highly associated with a larger amount of physical capital one period ago, this simply implies that investment will comparatively be smaller to physical capital if the amount of physical capital is larger. For debt over physical capital ($Debt_{i,t-2}/K_{i,t-2}$) we see that an increase in the debt ratio two years prior is linked to a small positive and significant effect on the investment ratio in the current year.

Conclusively, we cannot find evidence that patenting activity in general makes Norwegian companies less reliant on working capital in order to invest.

6.3 Size subset

Table 6.2: Model estimates on size subsets

	(1) Full Sample	(2) Small Subset	(3) Medium Subset	(4) Large Subset
$lnPATSTOCK_{i,t-1}$	0.103*	-0.090	0.222**	0.099
	(0.055)	(0.109)	(0.099)	(0.079)
$WCAP_{i,t-1}/K_{i,t-2}$	0.005**	0.007*	0.003	0.007
	(0.002)	(0.004)	(0.004)	(0.005)
$lnK_{i,t-2}$	-0.447***	-0.465***	-0.485***	-0.385***
	(0.034)	(0.049)	(0.049)	(0.080)
$DEBT_{i,t-1}/K_{i,t-2}$	0.014***	0.019**	0.015**	0.007
	(0.005)	(0.008)	(0.007)	(0.009)
$WCAPi,t-1/K_{i,t-2}\times$ $lnPATSTOCK_{i,t-1}$	-0.004	-0.011**	-0.004	0.000
	(0.002)	(0.005)	(0.004)	(0.003)
Time-fixed effects included?	Yes	Yes	Yes	Yes
Modified Wald test	9.6e+36***	6.5e+36***	1.4e+36***	9.4e+31***
	0.0000	0.0000	0.0000	0.0000
Wooldridge test	151.81***	138.84***	36.142***	0.84067
	0.0000	0.0000	0.0000	0.3592
Observations	8191	2303	3504	2343
Adjusted R^2	0.118	0.115	0.119	0.146

Heteroscedastic and serial correlation robust standard errors are reported in parentheses. Modified Wald test is testing for heteroscedasticity in the idiosyncratic errors. Wooldridge test is testing for serial correlation in the idiosyncratic errors. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

To test whether the effect differs between companies of different sizes, we ran the model on the company size subsets described in section 4.4.1. The results are presented in table 6.2. The effect of working capital only exhibits significant results for the small companies and the full sample. It does however only have a weak significance for the small subset, with a p-value of 0.072. The coefficient for the small subset is however larger than for the full sample. This finding might give some support to the rationale behind hypothesis two. If the small companies are more financially constrained, the effect of working capital should be greater than for the larger companies and the full sample.

For small and large companies, the coefficient of the $PATSTOCK$-variable is not significant. For medium companies, the coefficient is larger than for the full sample and significant at a 5 percent level. This suggests that a higher patenting activity has the most prevalent correlation to new investments in medium-sized companies. As mentioned, these effects can only be interpreted independently if either the *PATSTOCK* or *WCAP*-variable is equal to zero.

The effect of the interaction term is particularly interesting to our analysis. This is because it measures how the influence of internal liquidity on investments varies with different values of *PATSTOCK*. The effect is significant for small companies. Since the coefficient is negative, a higher *PATSTOCK*-value would lessen the effect of working capital. The findings are thus in accordance with hypothesis two, and partly hypothesis one. To understand the outcome we examine the total effect of working capital on investments, which due to the interaction term is given by equation 6.1.

$$0.005(\frac{WCAP}{K})_{i,t-1} - 0.004(\frac{WCAP}{K})_{i,t-1} \times ln(PATSTOCK)_{i,t-1} \tag{6.1}$$

The equation implies that if *PATSTOCK* and *WCAP* have values that are larger than zero the effect of working capital would be reduced by the negative interaction term. Furthermore, the effect of working capital would decrease progressively with higher *PATSTOCK*-values. This suggests that a company's investments are less sensitive to internal liquidity if they possess a larger number of patent applications. It does accordingly also have the reversed effect, where more internal capital would decrease the effect of patenting activity on investments.

6.4 Age subset

Table 6.3: Model estimates for age subsets

	(1) Age <= 10	(2) Age > 10
$lnPATSTOCK_{i,t-1}$	-0.080	0.056
	(0.129)	(0.053)
$WCAP_{i,t-1}/K_{i,t-2}$	-0.000	0.004*
	(0.003)	(0.002)
$lnK_{i,t-2}$	-0.518***	-0.399***
	(0.054)	(0.055)
$DEBT_{i,t-2}/K_{i,t-2}$	0.007	0.007
	(0.007)	(0.006)
$WCAPi,t-1/K_{i,t-2} \times lnPATSTOCK_{i,t-1}$	-0.003	-0.000
	(0.004)	(0.003)
Time-fixed effects included?	Yes	Yes
Modified Wald test	3.1e+36***	4.5e+37***
	0.0000	0.0000
Wooldridge test	220.28	108.15
	0.0000***	0.0000***
Observations	2941	5250
Adjusted R^2	0.112	0.096

Heteroscedastic and serial correlation robust standard errors are reported in parentheses. Modified Wald test is testing for heteroscedasticity in the idiosyncratic errors. Wooldridge test is testing for serial correlation in the idiosyncratic errors. * p<0.10, ** p<0.05, *** p<0.01

We investigate hypothesis three by examining companies subset by age. The results are presented in table 6.3. The group labelled as "young" consists of companies younger than 10 years, while the group named "established" consists of companies older than 10 years. We do not find evidence supporting the hypothesis that financial constraints in younger firms are more influenced by patenting activity, as the interaction term is non-significant for both subsets. Additionally, the findings only exhibit weak evidence for the effect of $WCAP$ in the established subset, and no significant results for the young subset.

The results might indicate that there is no significant relation between patenting activity and financial constraints for either of the age groups. However, the results may also be affected by the lack of companies under the age of two, as this entails that our dataset does not include the youngest companies. Additionally, there is a possibility that the assumption of a monotonic relationship between age and financial constraints is violated. This would entail that the placement of the cut-off points are influencing the results.

To further explore the relationship between financial constraint and age, we subset our datasets containing small, medium and large firms based on their age. The results are exhibited in appendix A2. We detect a significant effect of the interaction term for small companies that have been operating for more than 10 years. This finding might be due to the firm size itself being affected by financial constraints. We define company size by their last year observed in our sample. Younger companies that do seek to expand by investing in physical capital might therefore to some extent move to the medium-sized companies within the 10 years of the sample. The younger companies that are left in the small subsection after 10 years might therefore be companies lacking worthwhile investment opportunities.

Summarized, the results for the full sample indicate that the included companies are subject to financial constraints, but we do not get significant results for the interaction term. Investigating the size subsets our results imply that small companies are subject to more financial constraints and that patenting activity does alleviate financial constraints on physical investments in these companies. We do not find similar results for the medium or large companies. This supports hypothesis two, and gives partial support to hypothesis one. For the age subsets, we do not detect results that support hypothesis three.

7 Discussion

In this section, we discuss the potential implications of our findings, both from a theoretical and practical perspective. We also discuss the limitations of the paper, divided into limitations associated with the dataset, and limitations of the applied methodology. Lastly, we make suggestions for future research on the topic.

7.1 Implications of findings

7.1.1 Theoretical implications

This thesis contributes to the research field with evidence from a broad sample of companies in a Norwegian context. The comprehensive range of sectors gives an interesting perspective on the effect of patents in the economy as a whole, rather than limited to specific industries. Furthermore, as the research on the effect of patenting on financial constraints for companies beyond the start-up phase is more limited, it is particularly interesting that the findings also include established firms.

Our findings indicate that patenting activity contributes to alleviating financial constraints in smaller Norwegian R&D-active companies. This corresponds with the findings of Hottenrott et al. (2016), and corroborates the propositon that the alleviating effect of patents is greater in small companies, compared to larger companies. Due to differences in the data availability and estimation methods, we do however want to be cautious with comparing the magnitude of the effects. The findings also give support to the rationale presented by Long (2002), even if only for the small companies.

We do not find evidence supporting the expectation that younger companies are more likely to be financially constrained than established firms, or that patenting activity has more influence on financial constraints in young companies. Our findings are however in line with observations made in Czarnitzki and Hottenrott (2011) as well as Hottenrott et al. (2016). Nevertheless, our sample does not include companies under two years old, and there is a possibility of a non-monotonic relationship between financial constraints and age. This would entail that the placement of the cut-off points affects the results, and that there for instance could be constraints for even younger firms.

In regards to the underlying theory, that financial constraints affect smaller firms to a greater extent then larger firms, we can not present conclusive evidence [3]. The results indicate that the companies in the small subset and the full sample are financially constrained and that the constraints are greater in the small subset. This is consistent with Berger and Udell (1998;2002) as well as Hottenrott et al. (2016). The small subset does however only exhibit a weak significance for this variable. Since we do not find significant results for the large and medium companies we cannot draw conclusions from the results associated with these companies.

7.1.2 Practical implications

From a practical perspective, the findings could present new insights in the context of increasing R&D expenditure. If patents help alleviate financial constraints on investments in (small) R&D-active companies, there might exist opportunities in developing and improving the Norwegian patenting system. As discussed in section 2.1, the number of patent applications from Norwegian companies are decreasing, and a relatively small share of Norwegian innovative firms choose to use patents as their intellectual property strategy (The Research Council of Norway, 2019, 2020). The decreasing patent application numbers could indicate that the benefits of applying for patents are not considered great enough, compared to the effort and conditions accompanying patents and the application process.

Today, small companies are given some cost reductions when applying for patents. The costs do however seem to be predominantly fixed, especially when also considering costs associated with market research and development of the application (NIPO & Innovation Norway, n.d.). It would therefore be natural to assume that the application process commonly is comparatively more expensive for the smaller companies. If one would want to raise the number of patent applications, there would likely be benefits from investigating the possibility of making the process more accessible and less costly for small companies. However, there might exist a risk of an unintended consequence: If patenting becomes less expensive and more available, the signalling effect of attaining a patent could be reduced.

[3] In an alternate model specification we tried using cashflow instead of working capital as our measure of internal liquidity. We did not find any significant evidence for a varying degrees of financial constraints in the different firm-size subsets when applying robust standard errors. These findings are presented in appendix A3.

Denmark and Sweden both have a higher R&D expenditure to GDP ratio and a higher number of patent applications compared to Norway (OECD, 2021; WIPO, 2020). The similarities and differences in the patenting system of Norway and its neighbouring countries may serve to enlighten us as to the effects of these structures. Conducting an analysis on this topic may therefore provide valuable insight into why the current differences in patenting activity exist, as well as possibly uncovering potential areas of improvement for the Norwegian system.

In 2015, a law change made it possible to use patents, patent applications and licenses as collateral against debt in Norway. Formerly, it had been possible to use patents as collateral indirectly, but only as a part of the firms operating accessorises. The main motivation for the change was to make it easier for businesses to obtain funding to develop their invention (Norwegian Ministry of Justice and Public Security, 2014). One could argue that these changes illustrate that the role of patents in alleviating financial constraints has already been recognized to some extent. On the other hand, as of 2020, there were only 66 patents owned by Norwegian companies registered as being used as collateral.

There could be several explanations for why using patents as collateral is scarcely done. It may for instance be due to difficulties estimating the value of patents objectively or challenges with reselling the patents in the case of bankruptcy (Harhoff, 2009). This could indicate that the markets of intellectual property are not well-developed and still immature. Accordingly, we might see this practice becoming more prevalent when moving towards a knowledge-based economy. Harhoff (2009) argued that while the practice of using intellectual property as collateral against debt is not yet widespread, it should not be belittled, as it has «true potential and could make a major contribution in improving overall conditions for innovation».

7.2 Limitations

7.2.1 Limitations of data

Although the aim of our analysis is to identify if patenting activity can reduce financial constraints for Norwegian firms, the overarching economic matter is how to raise the level of R&D expenditure. In regards to this matter, the most central limitation to our analysis is the lack of data on R&D spending. We cannot with certainty claim that there is a direct connection between financial constraints on physical and R&D investments. However, due to the nature of R&D investments, it is natural to assume that if a company is subject to financial constraints on their physical investments, there are likely also financial constraints on their R&D investments.

With the available data, we are nevertheless not able to identify a direct relationship between financial constraints on R&D expenditure and former patenting activity. If we had access to data on R&D expenditure for Norwegian firms we would also have a well-defined selection criterion to create a data sample with all R&D-active companies. This would make it possible to approach the research question in alternative ways. We would for instance have the option of comparing financial constraints in patenting firms to financial constraints in non-patenting firms.

When working with accounting data there are some issues that might affect our analysis. Accounting practices can change within firms and differ between firms. How a variable is defined can thus vary over time and from company to company. This could create a challenge if, for instance, a firm goes from submitting their financial report in accordance with the Norwegian accounting standard to reporting under the IFRS system. The same accounting variable could therefore be defined differently over time. Accounting variables and identities are also susceptible to the firm's overall business strategy, for example in regards to pay-out policies, size of cash holdings and inventory. There is a possibility that our analysis is subject to biases related to this. This problem will to some extent be mitigated by the use of a fixed effect model, where the effects constant for the individual firms over time are removed. This will however not eliminate potential alterations occurring within a company during the sample period.

The analysis is also limited to patents applied for in Norway, as data on Norwegian companies filing for patents abroad is not included. This entails that the effect of foreign patents on financial constraints is not captured in the analysis. Another potential drawback is related to business groups. We have observed that for certain business groups the economic activity predominantly occurs in another company than the one that files for the patent. Under these circumstances, one firm will have rights to the patent, but have a separate subsidiary company where the actual economic activity takes place. In these cases, we will not be able to link the relationship between the patent and potential financial effects.

7.2.2 Limitations of estimation method

The applied estimation method is subject to several limitations. Because of the complex nature of firm investment behaviour, we cannot rule out the possibility of endogeneity in our model. We have aimed to reduce the endogeneity stemming from simultaneity and omitted variable bias. Due to the intertemporal nature of firms' physical investment strategy, the applied lagging of the explanatory variables might not remove all simultaneity. A fully dynamic investment model or the instrumental variable approach as the one implemented by Himmelberg (1994) or Scellato (2007) might therefore be preferable.

Another important aspect in removing endogeneity is to add theoretically sound control variables. In the current analysis, the controls employed should capture relevant information for the firms' future investment propensity, and thereby reduce the omitted variable bias for working capital's effect on investments. We can however not guarantee that the included control variables capture this information fully. An alternative would be to employ Tobin's q. Yet, as discussed in section 2.2.2 there is evidence suggesting that the variable is subject to several weaknesses, and due to the lack of publicly listed companies, it would not be applicable to our dataset [4].

Even if fully controlling for other factors in our model there are still some limitations that might affect the findings. The first potential shortcoming is related to the use of

[4]Following Himmelberg (1994) we tried a model specification including sales growth as a control variable. Due to varying accounting practices for sales revenue the construction of the variable would lead to a potential loss of otherwise valid observations. As it turned out to have little to no explanatory value in our model, we chose to not include this control.

segmenting variables and the selection of cut-off points. A main assumption of the model is that there is a monotonic relationship between financial constraints and the segment variables. If this is violated the placement of the segmenting cut-off could influence the results. Since we are not certain that the relationship between size and financial constraints as well as the relationship between age and financial constraints is monotonic, we cannot rule out the possibility that this affects our results.

Further, we conducted a $log(1 + X)$ transformation on the patent stock variable. This is unproblematic if the *PATSTOCK* variable is high enough, since $log(X)$ and $log(X + 1)$ converges with a high X. This could on the other hand cause problems for low or zero values of *PATSTOCK,* and may therefore influence the interpretation of the results.

There are also potential problems associated with the applied method of dealing with outliers. In ordinary least square models outliers have a large effect on coefficients, computed test statistics and are assumed to hold valuable information. In our case, it is apparent that the outliers are predominantly caused by the creation of ratio variables. We therefore find it unlikely that the magnitude of the majority of these extreme values provides relevant information within the framework of our analysis. Winzorising lets us retain information about the growth, while mitigating the vastness of the observations. The risk is however that the winzoring affects the validity of our coefficients and test statistics, as the sample potentially no longer reflects the population.

Lastly, there is a risk of reverse causality, where the financial constraints a firm is subject to affects the size of the firm. Interpreting a causal link between the segmenting variable and financial constraints can therefore be problematic. As our analysis aims to identify the degree to which patenting activity reduces financial constraints for the subsets by using an interaction term, the implications of reverse causality in the segmenting variable are somewhat reduced.

7.2.3 Future research

For future research, it would be particularly interesting to conduct a similar analysis on Norwegian R&D expenditure data. This would open new possibilities for how to investigate the research topic, as well as potentially validating the findings of the current study. There is however a scarcity of such data, especially on a non-anonymized firm-level. Studies like Hottenrott et al. (2016) have nonetheless been able to obtain R&D expenditure data from the OECD R&D-survey, even though these data are not usually available to external researchers.

Furthermore, including even younger companies in the sample could give a more comprehensive picture of the relationship between financial constraints, patenting and age. Another potential path of progression would be to investigate patenting's effect across sectors. How common it is to patent seems to vary between industries, and it would therefore be interesting to investigate whether patenting's effect on financial constraints also varies across industries, and if so, what factors that contribute to this.

To analyse whether the increase in external financing comes in the form of equity or debt financing would also be relevant. It could be interesting to investigate if the effect of patenting is strongest towards investors or debtors. This could also contribute to illuminate the potential of patents as collateral against debt, as the adoption of this practice still is limited in Norway. Within this topic, one could also construct a natural experiment exploring if the law change in 2015 had any significant effect on the degree to which patentees secure debt financing.

In our paper, we do not attempt to distinguish between the value of the inherent patented technology and the signalling value of applying for the patent. If one could assess the quality of the patented technology one might be able to disentangle the influence of the separate factors. Hottenrott et al. (2016) attempted to make such a separation by rating the quality of the patents based on the number of forward citations. Such an approach might be adaptable to a Norwegian context.

8 Conclusion

The aim of this thesis has been to investigate patents' effect on financial constraints for a sample of Norwegian companies in the period between 2009 and 2018. The fundament of the analysis was the following research question: *Does patenting activity affect financial constraints in Norwegian companies?* Based on the research question and theoretical background, we develop three hypotheses. The main hypothesis was: *Norwegian companies with a higher degree of prior patenting activity will be subject to less financial constraints, compared to firms with less prior patenting activity.* This was supplemented with two subhypotheses, concerning the size and age of the companies.

In order to explore the hypotheses, we applied a fixed effect regression to a panel consisting of company, accounting and patent application data. Inspired by the method presented in Hottenrott et al. (2016) we investigated how physical investments' sensitivity to internal liquidity varies with different levels of patenting activity.

The findings indicate that patenting activity does have a significant effect on financial constraints in small companies. We did not detect similar results for the medium or large companies. In other words, we find support for hypothesis two and limited support for hypothesis one. We did not find significant results for neither established nor young firms, meaning that there was no evidence supporting hypothesis three. Conclusively, the analysis suggests that for small Norwegian companies a higher degree of patenting activity alleviates financial constraints on investments. This corresponds with the findings of Hottenrott et al. (2016), and offers support to the propositon that the alleviating effect of patents is the most substantial in small companies.

Since the Norwegian Government has an objective to increase domestic R&D expenditure, particularly with a need for greater investments from the private sector, we argue that these findings provide insights of broad interest. If patenting does lead to an increased willingness to invest in small R&D-active companies, facilitating for increased patenting activity may have a positive influence on domestic R&D expenditure.

References

Alti, A. (2003). How sensitive is investment to cash flow when financing is frictionless? *The journal of finance, 58*(2), 707-722.

Altinn. (2020). Patents. Retrieved from https://www.altinn.no/en/start-and-run-business/planning-starting/protection-of-rights/patents/

Baum, C. F. (2001). Residual diagnostics for cross-section time series regression models. *The Stata Journal, 1*(1), 101-104.

Baum, J. A. C., & Silverman, B. S. (2004). Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. *Evolutionary approaches to entrepreneurship: Honoring Howard Aldrich*, *19*(3), 411-436.

Berger, A., & Udell, G. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of Banking & Finance, 22*(6-8), 613-673.

Berger, A., & Udell, G. (2002). Small business credit availability and relationship lending: The importance of bank organisational structure. *The economic journal, 112*(477), F32-F53.

Berner, E., Mjøs, A., & Olving, M. (2016). *Norwegian Corporate Accounts - Documentation and quality assurance of SNF's and NHH's database of accounting and company information for Norwegian companies.*

Blundell, R., Bond, S., Devereux, M., & Schiantarelli, F. (1992). Investment and Tobin's Q: Evidence from company panel data. Journal of econometrics, 51(1-2), 233-257.

Carreira, C., & Silva, F. (2010). No deep pockets: some stylized empirical results on firms' financial constraints. *Journal of Economic Surveys, 24*(4), 731-753.

Chirinko, R. S. (1993). Business fixed investment spending: Modeling strategies, empirical results, and policy implications. *Journal of Economic literature, 31*(4), 1875-1911.

Clapham, C. (2001). *Oxford concise dictionary of mathematics:* Shanghai Foreign Language Education Press.

Czarnitzki, D., Hall, B., & Oriani, R. (2006). The Market Valuation of Knowledge Assets in US and European Firms. In D. Bosworth & E. Webster (Eds.), *The Management of Intellectual Property* (pp. 111- 131). UK: Edward Elgar Publishing.

Czarnitzki, D., & Hottenrott, H. (2011). R&D investment and financing constraints of small and medium-sized firms. *Small business economics, 36*(1), 65-83.

Deeds, D. L., Decarolis, D., & Coombs, J. E. (1997). The impact of firmspecific capabilities on the amount of capital raised in an initial public offering: Evidence from the biotechnology industry. *Journal of Business Venturing, 12*(1), 31-46.

Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *The Stata Journal, 3*(2), 168-177.

Farre-Mensa, J., & Ljungqvist, A. (2016). Do Measures of Financial Constraints Measure Financial Constraints? The Review of Financial Studies, 29(2), 271-308.

Fazzari, S., Hubbard, R., & Petersen, B. (1988). Financing Constraints and Corporate Investment. *National Bureau of Economic Research Working Paper Series, 1.*

Griliches, Z. & Mairesse, J. (1984). *Productivity and R&D at the Firm Level*, in: Griliches Z. (ed.), R&D, Patents, and Productivity. Chicago, University of Chicago Press.

Haeussler, C., Harhoff, D., & Mueller, E. (2009). To Be Financed or Not: The Role of Patents for Venture Capital Financing. Retrieved from ZEW Discussion Papers: ftp://ftp.zew.de/pub/zew-docs/dp/dp09003.pdf

Hall, B. (1999). Innovation and Market Value. *National Bureau of Economic Research Working Paper Series, 6984.*

Hall, B., Helmers, C., Juster, T., & Sena, V. (2013). The Importance (or Not) of Patents to UK Firms. *Oxford Economic Papers, 65.*

Hall, B., Jaffe, A., & Trajtenberg, M. (2005). Market Value and Patent Citations. *The RAND Journal of Economics, 36*(1), 16-38.

Hall, B. H., & Kruiniker, H. (1995). The role of working capital in the investment process. In: Investment, R&D, and the Financing Decisions of the Firm. pp. 117–152 (Chapter 5).

Hall, R. (1992). The strategic analysis of intangible resources. *Strategic Management Journal, 13*(2), 135-144.

Harhoff, D. (2009). The role of patents and licenses in securing external finance for innovation. *EIB Papers* (11/2009).

Hart, O., & Moore, J. (1995). Debt and seniority: An analysis of the role of hard claims in constraining management. *The American Economic Review, 85*(3), 567-585.

Hayashi, F. (1982). Tobin's marginal q and average q: A neoclassical interpretation. *Econometrica: Journal of the Econometric Society*, 213-224.

Heeley, M., Matusik, S., & Jain, N. (2009). Innovation, Appropriability, And The Underpricing Of Initial Public Offerings. *The Academy of Management Journal 50*(1).

Helmers, C., & Rogers, M. (2011). Does patenting help high-tech start-ups? *Research Policy, 40*(7), 1016-1027.

Himmelberg, C. P., & Petersen, B. (1994). R&D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries. *The Review of Economics and Statistics, 76*(1), 38-51.

Hottenrott, H., Hall, B., & Czarnitzki, D. (2016). Patents as quality signals? The implications for financing constraints on R&D. *Economics of Innovation and New Technology, 25*(3), 197-217.

Hsu, D. H., & Ziedonis, R. H. (2013). Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. *Strategic Management Journal, 34*(7), 761-781.

Kaplan, S. N., & Zingales, L. (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The quarterly journal of economics, 112*(1), 169-215.

Lamont, O., Polk, C., & Saaá-Requejo, J. (2001). Financial constraints and stock returns. *The review of financial studies, 14*(2), 529-554.

Leland, H. E., & Pyle, D. H. C. (1977). Informational Asymmetries, Financial Structure, and Financial Intermediation. *The Journal of Finance, 32*(2), 371-387.

Long, C. C. (2002). Patent Signals. *The University of Chicago Law Review, 69*(2), 625-679.

Mann, R. J., & Sager, T. W. (2007). Patents, venture capital, and software start-ups. *Research Policy, 36*(2), 193-208.

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

NIPO. (2016). What can be patented? Retrieved from https://www.patentstyret.no/en/services/patents/what-can-be-patented/

NIPO. (2017). Applying for a patent abroad. Retrieved from https://www.patentstyret.no/en/services/patents/applying-for-a-patent-in-other-countries/applying-for-a-patent-abroad/

NIPO. (2019). *Årsrapport 2018*. Retrieved from https://www.patentstyret.no/globalassets/om-oss/aarsrapporter/patentstyrets-arsrapport-2018.pdf

NIPO. (2020a). Application process for a patent. Retrieved from https://www.patentstyret.no/en/services/patents/application-process-for-a-patent/

NIPO. (2020b). European patent application. Retrieved from https://www.patentstyret.no/en/services/patents/applying-for-a-patent-in-other-countries/european-patent-application/

NIPO. (2020c). *Årsrapport 2019.* Retrieved from https://www.patentstyret.no/globalassets/om-oss/aarsrapporter/patentstyret_aarsrapport_2019.pdf

NIPO, & Innovation Norway. (n.d.). Patentkalkulator.

Norwegian Ministry of Education and Research. (2018). Langtidsplan for forskning og høyere utdanning 2019–2028. In *Meld. St. 4 (2018–2019).*

Norwegian Ministry of Justice and Public Security. (2014). *Endringer i panteloven m.m. (pant i patenter og planteforedlerretter).* (Prop. 101 L). Retrieved from https://www.regjeringen.no/contentassets/638be393addd44a7a6675833cb901627/no/pdfs/prp201320140101000dddpdfs.pdf

NOU2016:3. (2016). *Ved et vendepunkt: Fra ressursøkonomi til kunnskapsøkonomi.* Retrieved from https://www.regjeringen.no/no/dokumenter/nou-2016-3/id2474809/?ch=1

OECD. (2007). *Innovation and Growth - Rationale for an innovation strategy.* Retrieved from https://www.oecd.org/sti/39374789.pdf

OECD. (2015). *The Innovation Imperative.* Retrieved from https://www.oecd-ilibrary.org/content/publication/9789264239814-en

OECD. (2021). *Main Science and Technology* Indicators (Vol. 2020 (2)). Paris: OECD Publishing.

Orbis. (n.d.). Company size classification. Retrieved from https://help-bvdinfo-com.ezproxy.nhh.no/LearningZone/Products/orbis4.1/Content/I_Data/Company/SizeClassification.htm?cshid=11001

The Norwegian Patents Act. (1967). The Norwegian Patents Act (LOV-1967-12-15-9). Retrieved from https://lovdata.no/dokument/NL/lov/1967-12-15-9

Romer, P. M. (1990). Endogenous technological change. Journal of political Economy, 98(5, Part 2), 71-102.

Scellato, G. (2007). Patents, firm size and financial constraints: an empirical analysis for a panel of Italian manufacturing firms. *Cambridge Journal of Economics 31*(1), 55-76.

Schumpeter, J. A. (1942). *Capitalism, Socialism, and Democracy.* New York: Harper and Row.

Seymore, S. B. (2010). The Teaching Function of Patents. *Notre Dame Law Review 85*(2), 621-669.

Silva, F., & Carreira, C. (2012). Measuring Firms' Financial Constraints: A Rough Guide. *Notas Económicas, 36*(2012-14), 23–46.

The Research Council of Norway. (2019). *Det norske forsknings- og innovasjonssystemet – statistikk og indikatorer 2019*. Retrieved from https://www.forskningsradet.no/contentassets/bf27e2b74690414c93a235bbb294f59d/indikatorrapporten-2019_endelig_291119.pdf

The Research Council of Norway. (2020). *Det norske forsknings- og innovasjonssystemet – statistikk og indikatorer 2020*. Retrieved from https://www.forskningsradet.no/contentassets/f9c1e76a01df4f519cfbd741347987e3/indikatorrapporten-2020-002.pdf

Tirole, J. (2006). *The Theory Of Corporate Finance*. Princeton, N.J: Princeton University Press.

Wagner, S., & Cockburn, I. (2010). Patents and the survival of Internet-related IPOs. *Research Policy, 39*(2), 214-228.

WIPO. (2020). *World Intellectual Property Indicators 2020*. Geneva: World Intellectual Property Organization.

Wooldridge, J. M. (2013). *Introductory econometrics : a modern approach* (5th ed.). Mason, Ohio: South-Western, Cengage Learning.

Appendix

A1 Data cleaning progression

Table A1.1: Data cleaning progress

	Data source	Nr. of observations	Nr. of companies	Nr. of patent applications
	NIPO dataset	7164	2109	7164
	SNF accounting dataset	3,305,311	498,294	NA
	SNF company dataset	3,294,379	496,665	NA
	Data cleaning steps			
1	Merged file	17,383	2,000	5,599
2	Removing PATAPPS=0	17,109	1,950	5,599
3	Removing companies with investments or operating revenue = 0 for all years	13,307	1,512	4,754
4	Removing companies with < 0 sales revenue, debt and total assets	13,251	1,508	4,741
5	Removing companies with physical capital stock =< 0	11,264	1,407	4,195
6	Lagging	9,157	1,352	3216
7	Deleting observations with NA-values in main variables	8,191	1,224	2,923
	Total included	8,191	1,224	2,923

A2 Regression table age and size subsets

Table A2.1: Model estimates on age and size segmented subsets

	(1) Full Sample Young	(2) Full Sample Established	(3) Small Young	(4) Small Established	(5) Medium Young	(6) Medium Established	(7) Large Young	(8) Large Established
$lnPATSTOCK_{i,t-1}$	-0.080	0.056	-0.317*	0.065	0.233	-0.049	-0.234	0.046
	(0.129)	(0.053)	(0.178)	(0.169)	(0.216)	(0.107)	(0.156)	(0.071)
$WCAP_{i,t-1}/K_{i,t-2}$	-0.000	0.004*	0.001	0.008*	-0.001	0.002	-0.011	-0.001
	(0.003)	(0.002)	(0.005)	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)
$lnK_{i,t-2}$	-0.518***	-0.399***	-0.502***	-0.378***	-0.511***	-0.442***	-0.475***	-0.353***
	(0.054)	(0.055)	(0.084)	(0.082)	(0.079)	(0.080)	(0.173)	(0.108)
$DEBT_{i,t-2}/K_{i,t-2}$	0.007	0.007	0.008	0.009	0.000	0.011	0.001	-0.008
	(0.007)	(0.006)	(0.011)	(0.010)	(0.010)	(0.010)	(0.014)	(0.010)
$WCAP_{i,t-1}/K_{i,t-2}\times lnPATSTOCK_{i,t-1}$	-0.003	-0.000	-0.006	-0.014**	-0.000	0.005	0.007	0.002
	(0.004)	(0.003)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Time-fixed effects included?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.112	0.096	0.089	0.111	0.106	0.110	0.194	0.072
Observations	2941	5250	1216	1087	1301	2203	256	1553

Heteroscedastic and serial correlation robust standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01

A3 Regression with cashflow as internal liquidity variable

In this appendix we show an alternate model specification where we deploy cashflow as our measure of internal capital. This is in line with the with the seminal papers studying financial constraints. Using cashflow as our internal capital measure we cannot find any significant effects for the PATSTOCK-variable, the interaction term or for cashflow itself. HAC-robust standard errors are applied.

Table A3.1: Model estimates on size subsets using cashflow

	(1) Full Sample	(2) Small Subset	(3) Medium Subset	(4) Large Subset
$lnPATSTOCK_{i,t-1}$	0.055	-0.120	0.142	0.092
	(0.051)	(0.126)	(0.088)	(0.058)
$CF_{i,t-1}/K_{i,t-2}$	0.000***	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$lnK_{i,t-2}$	-0.493***	-0.509***	-0.525***	-0.433***
	(0.018)	(0.039)	(0.029)	(0.028)
$DEBT_{i,t-2}/K_{i,t-2}$	0.005*	0.009*	-0.001	0.006
	(0.003)	(0.005)	(0.004)	(0.004)
$CF_{i,t-1}/K_{i,t-2}\times$ $lnPATSTOCK_{i,t-1}$	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Time-fixed effects included?	Yes	Yes	Yes	Yes
Observations	8191	2303	3504	2343
Adjusted R^2	-0.041	-0.109	-0.025	0.021

Heteroscedastic and serial correlation robust standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01

A4 Random effect model

In this appendix we will investigate if it is appropriate to use a random effect model instead of a fixed effect model. One of the drawbacks of using the fixed effect model is that it requires a large number of parameters to be calculated, which consumes degrees of freedom. It would therefore be of interest to utilize a more efficient estimation technique (Wooldridge, 2013, p. 484-486).

Instead of fully time-demeaning the variables, the random effect model only quasi-demeans them. The model also rely on less parameters to be estimated and therefore consumes fewer degrees of freedom, making the random effect model more efficient in estimating coefficients. Due to the inclusion of some variation in α_{it} the random effect model rely on the assumption of strict exogeneity between the explanatory variables and α_{it}, in order to be unbiased and efficient (Wooldridge, 2013, p. 492-495).

To test the assumption of strict exogeneity we deploy a Hausman test (Wooldridge, 2013, p. 496). In contrast to random effect model the fixed effect model is unbiased even when there is correlation between the explanatory variables and α_{it}. We can therefore compare the coefficient vectors of the fixed effect model and the random effect model. If they are equal, we can apply a random effect model.

The Hausman test is presented in table A5.1 for the full sample and the subsets segmented on size. All regressions are run and presented with default standard errors as robust standard errors would cause the Hausman statistic to lose its chi-square distribution. As the Hausman test finds a significant difference in the coefficients for the full sample and for all of our size subsets. We can therefore not rely on a random effects model in our analysis. This is in line with our expectations as it is natural to assume that the working capital ratio, firm patenting propensity and debt ratio is correlated with the error term α_{it}. This is because α_{it} includes a large number of observable and unobservable firm-characteristics such as industry or managerial ability.

Table A4.1: Model estimates with random effect on size subsets

	(1) Full Sample Fixed effect	(2) Full Sample Random effect	(3) Small Subset Fixed effect	(4) Small Subset Random effect	(5) Medium Subset Fixed effect	(6) Medium Subset Random effect	(7) Large Subset Fixed effect	(8) Large Subset Random effect
$lnPATSTOCK_{i,t-1}$	0.103**	0.166***	-0.090	0.042	0.222**	0.206***	0.099*	0.090**
	(0.052)	(0.041)	(0.133)	(0.109)	(0.094)	(0.075)	(0.059)	(0.043)
$WCAP_{i,t-1}/K_{i,t-2}$	0.005***	0.009***	0.007**	0.007***	0.003	0.003	0.007***	0.006***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$lnK_{i,t-2}$	-0.447***	-0.205***	-0.465***	-0.310***	-0.485***	-0.383***	-0.385***	-0.230***
	(0.020)	(0.011)	(0.043)	(0.030)	(0.032)	(0.023)	(0.028)	(0.018)
$DEBT_{i,t-2}/K_{i,t-2}$	0.014***	0.027***	0.019***	0.024***	0.015***	0.025***	0.007*	0.016***
	(0.003)	(0.002)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)
$WCAPi,t/K_{i,t}\times$ $logPATSTOCK_{i,t-1}$	-0.004***	-0.004***	-0.011***	-0.011***	-0.004*	-0.005**	0.000	0.002
	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	4.097***	2.084***	3.487***	2.460***	4.192***	3.447***	4.500***	2.817***
	(0.169)	(0.102)	(0.290)	(0.218)	(0.262)	(0.201)	(0.311)	(0.211)
Time-fixed effects included?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hausman test		249.32***		NA		50.29***		131.51***
		0.0000		NA		0.0000		0.0000
Observations	8191	8191	2303	2303	3504	3504	2343	2343
Adjusted R^2	-0.037		-0.100		-0.024		0.030	

Default standard errors are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$