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Patent Activity and Startup Funding in Sweden

An empirical study conducted on Swedish startups

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Abstract

We run a multiple linear regression model to test (1) whether filing at least one patent application before the first round of funding increases startups' first-round funding amount and (2) whether the number of filed patent applications before the first funding round increases startups first-round funding amount. We apply a dataset of Swedish startups founded between 1990-2007.

Our findings suggest that successful patent applications increase the amount of startup funding in the first round. Having filed at least one patent application increases the first-round funding amount by 54.3% compared to their non-patenting counterparts. In addition, we find that a one standard deviation increase in the number of patent applications increases the funding amount by 14.9%, compared to its mean. These results imply that patents reduce the information asymmetries between startups and investors and that investors value startups with innovative activity, which can have important implications for Swedish startups. Even though patents are suggested to reduce information asymmetries and thus increase investors' first-round funding, further research is suggested to account for additional financing drivers, besides the ones accounted for in this study.

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1. Introduction

Stockholm, the Swedish capital, ranked the second highest producer of private startups worth more than one billion USD (“unicorns") per capita globally in 2015 (Knowledge@Wharton, 2015). The country has fostered some of Europe’s largest technology companies, such as Spotify, Skype, and Klarna (McKenna, 2017). The high production of successful startups is still an ongoing trend in Sweden. The Swedish Institute (2021) reports that Sweden invests approximately 3% of its GDP in research and development. Furthermore, according to the European Commission, Sweden’s innovation performance exceeded the average in the remaining EU countries in 2020, measured above 125% (Hollanders, Es-Sadki, Merkelbach, & Khalilova, 2020).

Despite the high number of successful startups, any startup faces challenges regarding liquidity in the early phases. Thus, they rely on external sources of funding to survive (Lee & Zhang, 2011). Taking on debt from commercial banks in Sweden might be expensive and go on the expense of the entrepreneur(s) personal finance if the startup goes bankrupt (Knowledge@Wharton, 2015). Thus, equity investments through friends and family, angel investors, and venture capitalists, among others, are the preferred type of startup funding (Corrales-Estrada, 2019).

However, due to a lack of financial history and extensive information asymmetries, such funding types can be challenging to attract, especially in early stages (Damodaran, 2009). Within the entrepreneurial finance literature, many researchers have found that patents serve a signaling effect and can reduce information asymmetries and provide startups with economic benefits and legal protection. Patents have proven effective in terms of increased perceptions of startup value from venture capitalists, especially in early stages (Hsu & Ziedonis, 2008, 2013). Further, the intellectual property (IP) right contribute positively in attracting venture capital funding and significantly increased investment amounts from venture capitalists (Baum & Silverman, 2004; Cockburn & MacGarvie, 2009; Conti, Thursby, & Rothaermel, 2013; Hoenen, Kolympiris, Schoenmakers, & Kalaitzandonakes, 2014; Mann & Sager, 2007; Zhou, Sandner, Martinelli, & Block, 2016)

However, research on patents’ effect on other types of startup funding is somewhat scarce. Some researchers have examined the effect of patents on angel investments with mixed results

(Conti et al., 2013; Graham, Merges, Samuelson, & Sichelman, 2009; Sudek, 2007), while the remaining types of startup funding have, until now, remained left in the dark.

To our knowledge, no study has been conducted on the relationship between patents and the amount of startup funding raised across funding types. The primary motivation of this thesis is to contribute to this existing gap in the entrepreneurial finance literature. In line with previous research on venture capital funding, we argue that patents should positively impact the amount of startup funding across funding types as well, as the IP-right can serve a signaling purpose and reduce information asymmetries between startups and investors. Additionally, we have not seen any study that addresses the impact of patents on startup funding in either of the Nordic countries in isolation. Motivated by this fact, the unicorn factory Sweden is an exciting starting point since their innovation performance is high, as explained above.

Thus, based on the existing gap, and the non-existing literature, we formulate our main hypothesis:

Hypothesis 1: Patenting activity, as measured through at least one filed patent application, positively affects the amount of first-round funding for Swedish startups.

Additionally, to examine whether the number of applications affects the amount of startup funding raised, we articulate a second hypothesis:

Hypothesis 2: The number of filed patent applications positively affects the amount of first-round funding for Swedish startups.

In our opinion, there are at least two reasons why we should expect a positive effect of patenting activity on the amount of first-round startup funding. First, patent applications may help the startup in securing future financing, as they serve a signaling purpose that reduces information asymmetries. Second, in the first funding round for startups with patenting activities, the dollar amount of funds raised should be more generous, as patents can reflect startup qualities that are necessary for startup survival.

We test our hypotheses applying a dataset of 132 Swedish startups founded between 1990-2007, retrieved from Crunchbase. The startups in our sample received their first-round funding during the period 2000-2019. We manually collect data on filed patent applications between 1990-2020 from the United States Patent and Trademark Office (USPTO).

After running a multiple linear regression model, controlling for financing drivers, our results suggest that filing a patent application before the first round of financing increases the amount of first-round startup funding by 54.3% across funding types. Further, a one standard deviation increase in the number of filed patent applications before first-round funding leads to a 14.9% increase in funding amount, compared to its mean.

Our results suggest that patents work as an effective signal that reduces information asymmetries and reflects startup quality which seems to be valued by investors. Thus, the implications of our results suggest that patenting activity comes with additional economic benefits in the first round of funding across startup funding types in Sweden. Swedish entrepreneurs can maintain the probability of startup survival by applying for patents and thus secure equity investments, avoiding taking on expensive debt. Further, our results suggest that investors value high innovative activity and thus provide more considerable amounts of startup funding when the startup files more patent applications.

Our thesis is structured as follows. Section 2 presents previous research on the topic. In section 3, we present our data collection. Following, section 4 explains the methodology and variables used in our models. In section 5, we provide an empirical analysis and results. Section 6 provides a discussion and the implications of our results. Section 7 touches upon potential limitations and provides suggestions for further research. Finally, we conclude the thesis in Section 8.

2. Literature Review

This section provides insight into previous research on the impact of patents on startup funding. The literature review is divided into two sections. First, we explain the problems with information asymmetries between entrepreneurs and investors. Subsequently, we turn to signal theory as a solution to the problem of asymmetric information. We explain the basic concept and dive into research done on patents' effect on startup funding.

2.1 Asymmetric Information

Information asymmetries are a common problem that results from one party in a transaction having more and better information than the other party. Asymmetric information is one of the major problems concerning uncertainties regarding quality. The concept applies to several actors in different markets (Akerlof, 1970), including the relationship between investors and entrepreneurs seeking external capital.

Attracting financing is crucial for the startup during the early stages to further develop and ultimately survive. When seeking external financing, it can be difficult and expensive to raise capital from traditional sources such as commercial banks. The reason is that startups are characterized by high uncertainty and are constrained regarding financial resources. Therefore, startups must turn to other sources of external capital to obtain a chance to survive (Lee & Zhang, 2011).

Private equity sources such as friends, family, angels, and venture capitalists can offer startups the capital they need. However, the relationship between entrepreneurs and investors is characterized by information asymmetries since startups typically suffer from negative cash flows. Its performance and prospects are thus challenging to assess for any outsiders (Damodaran, 2009; Haeussler, Harhoff, & Mueller, 2014). Thus, the startup needs to reduce the information asymmetry by efficiently communicating its quality to potential investors.

2.2 Signal Effects

Entrepreneurs can reduce information asymmetries through signaling, which, in the literature, is viewed as an effective mechanism of communication.

According to Spence (1973), a signal is one or more visible attributes that act as pointers of one or more adjustable but unobservable characteristics of a signaler. For a signal to be efficient, it should be costly to obtain for the signaler. Further, it should be of low cost for the receiver to obtain the signal, and it shall enable the receiver to distinguish between quality types (Long, 2002). Going forward, we will refer to the startup as the signaler and a new investor the receiver of the signal, in line with previous research on signaling within the entrepreneurial finance literature (Connelly, Certo, Ireland, & Reutzel, 2011). Previous work has applied Spence's theory in the context of patents as an effective signal to attract investors.

Long (2002) argues that patents can serve as a signal. Even though patents come with the benefit of the right to exclude competitors and thus legal protection, less visible characteristics of a startup, such as firm or innovation productivity or other types of knowledge capital, can also be revealed through patents. If investors recognize that patents can serve such a purpose, the IP-right can assist startups in conveying information that is not easy to identify for investors. We argue, in line with the literature, that patents fulfill the criteria that form a signal. First, for potential investors, the cost of obtaining the information from a patent is relatively low, as they are publicly available sometime after the filing date. Second, patents are costly to obtain for the startup in filing fees and application processing time, meaning only startups with high-quality inventions will be willing to apply. Finally, patents can be associated with characteristics of a startup that can be challenging to identify and that is valuable to investors (Long, 2002).

The literature on patents as a signaling mechanism for startup funding has mostly focused on venture capital funding. Some but little attention has been dedicated to other types of startup funding. One reason might be that it previously has been difficult to get credible data on specific deals from private investors, as some prefer to stay anonymous (Van Osnabrugge & Robinson, 2000).

Results of the 2008 Berkeley Patent Survey (2009) suggest that the motivation of a technology startup to apply for patents is varied. Among them is the incentive to achieve the startup's financial goals. The study surveyed 1,332 young US-based companies. The respondents' perception was that patents contribute to the decision of funding across several startup funding types, such as angel investors, friends, family, venture capitalists, commercial banks, and investment banks (Graham et al., 2009). The authors have further conducted interviews on a sample of the entrepreneurs enrolled in the survey, which is advantageous. From the entrepreneurs, they got first-hand information, providing an accurate picture of the perception of patents' effect on attracting funding. However, to our understanding, the authors did not consult any of the funding sources directly concerning the importance of patents in the investment decision. Thus, there might exist some alternative explanation, besides patents, that serves as investor's determination standard.

Also, research that has been dedicated to the investment decision criteria of an investor has mainly focused on the selection criteria of venture capitalists. However, in a mixed study of angel investors, Sudek (2007) report that IP rights, such as patents, were infrequently mentioned as a selection criterion during interviews with 72 members from the Tech Coast Angels. This finding suggests that for angel investors, patents as a selection criterion to invest in a startup varies across investors. The results, however, highlighted the entrepreneur's passion, trustworthiness, the appropriability of the management team, and exit strategy as criteria for investing (Sudek, 2007). The findings, therefore, contradict what was uncovered by Graham et al. (2009).

Conti et al. (2013) introduces a simple model suggesting that startups should invest in the signal their targeted investor value the most. The authors empirically test the model using a sample of high technology companies from the Advanced Technology Development Center in Georgia. They test the effect of technological quality signaling through patents and founder commitment signaling through investments of friends, family, and founder (FFF) funds on venture capitalist and business angel funding, respectively. The results suggest that venture capitalists and business angels value different signals when facing an investment decision. They find that "a 1% increase in the number of patents filed increases the likelihood of venture capital financing by 46%, while a 1% increase in FFF money increases the likelihood of business angel financing by 5%" (Conti et al., 2013, p. 343). The research, therefore, contradicts the reported perceptions on the importance of patents in the investment decision as explained by Graham et al. (2009) and is consistent with the findings of Sudek (2007).

A vast majority of research is dedicated to patents' effect on venture capital funding, regarding the probability of receiving funding, investor's valuation estimates of startups, and the funding amount raised. These studies have mainly focused on industries where patenting activity is shown to be relatively high (Nadeau, 2010). For example, Cockburn and MacGarvie (2009) and Mann and Sager (2007) investigates patenting activity in the software industry. For startups in the this industry, venture capital funding increased by 15% for one additional patent application (Cockburn & MacGarvie, 2009). Additionally, software startups that engaged in patenting activity received approximately 10.7M USD more in venture capital funding compared to non-patenting startups (Mann & Sager, 2007). For patenting startups in the biotechnology industry in Canada, patent applications are shown to lead to significantly more venture capital funding (Baum & Silverman, 2004). Hsu and Ziedonis (2008, 2013) investigate whether patents assist startups in the semiconductor industry in the United States (US) in attracting venture capital funding. They find that patents increase startup valuation estimates by 28% for a doubling in the number of filed patent applications, and that valuation estimates seem to be higher in the early stages (Hsu & Ziedonis, 2008, 2013) .

All the studies mentioned above find a positive relationship between patenting activity on venture capital funding, with various results regarding the size of the economic impact. However, it is reasonable to assume that startups in industries with high levels of patenting activity have higher innovation productivity, which might be considered a valuable characteristic by investors, however, difficult to observe. High innovation productivity can be reflected through multiple patent applications and thus constitute effective signals. Thus, one can argue that a positive effect on funding is expected.

An interesting finding when examining 580 US-based biotechnology startups, Hoenen et al. (2014) reveals that patenting activities before the first round of funding increase the amount raised from venture capitalists for each additional patent compared to patenting activities before the second round of financing. The economic size equaled an increase of 7.7% first-round funding for each additional application. In other words, startups receive more in first-round funding than what is provided in the second round if the startup files for at least one patent application. Their findings suggest that patents have a higher value during the first round of venture capital funding when information asymmetries are high. That is, a patent application loses value between the first and the second round of venture capital financing as the investor gets more familiar with the startup (Hoenen et al., 2014).

A limited number of studies have also investigated the signaling effect of patents on venture capital funding across sectors. Zhou et al. (2016) examined whether patents and trademarks together served an even more substantial signaling effect than each IP right alone. The authors uncovered that for the technology startups in their sample, patents and trademarks are more efficient in attracting venture capital funding when combined, rather than each IP-right alone. However, they also found that applying only for at least one patent before turning to venture capitalists for capital increased the funding amount by 51.7%. This significant effect is consistent with Hoenen et al. (2014) finding that patent applications before the first round of funding attracts higher amounts of venture capital funding and strengthen the suggestion that patents assist startups in reducing information asymmetries when these are severe, in line with previous literature.

Caviggioli, Colombelli, De Marco, and Paolucci (2020) conducted an extensive study on 1,096 young innovative companies in Europe. They broke the signaling effect of patents into measures of complexity, portfolio size, and quality. They examined whether any of these characteristics had a positive effect on venture capital funding across sectors, in specific industries, and during different stages of funding. The results suggest that the number of filed patent applications and quality measures attracts higher amounts of venture capital funding across sectors. When comparing sectors with different levels of IP intensity, the results suggest that patenting activity is more valuable for attracting funding in industries with high IP intensity. Finally, the authors uncover that more patent applications during early financing rounds are not significant on the amount raised (Caviggioli et al., 2020). This latter finding contradicts the findings of Hoenen et al. (2014) and Zhou et al. (2016), explained above. Nevertheless, a weakness of the study is that the authors apply a sample of only the largest venture-backed deals listed in VCStar. In our opinion, this might create a skewed image of what reality looks like in Europe, as the characteristics discussed in the paper might not apply to all sizes of funding.

Our thesis differentiates from the studies mentioned above in several aspects. First, we have restricted our research objective to Sweden. To our knowledge, no studies on the economic impact of patenting activities on startup funding have been done in either of the Nordic countries in isolation. We argue that Sweden is a good point of departure as the country has favorable policies for young companies (Løhre, 2015). Second, a large portion of the research has focused on venture capital funding. Such funding is challenging to attract for startups due to their reliance on due diligence and involvement of the venture capitalists in the startup's operations through monitoring (Gompers & Lerner, 2001). Even though the emphasis on venture capital funding is reasonable, we account for other funding types as well.

Further, information asymmetries are shown to be more severe during the early stages of financing. We focus our thesis on whether patents attract more startup funding in the first round of financing across funding types and industries. Since Sweden generates many startups, investors need to find ways to distinguish the high-quality ones from the lower quality ones without excessive effort, and patents are suggested to serve such a purpose. Even though angel investors do not consider patents an investment decision criterion, as explained above, we still want to test whether this holds for Swedish startups as well. In addition, before investigating specific types of funding or industries, the chapter on the overall effect of patents on the amount of startup funding has to be opened in Sweden. Finally, we differentiate from previous research in that we apply a dataset from Crunchbase. The database is barely used in studies like those mentioned, as most researchers apply data from more famous sources, such as VentureXpert.

As a final remark, Farre-Mensa, Hegde, and Ljungqvist (2020) found that being a first-time applicant who "wins" what they refer to as the "patent lottery" increases the probability of receiving funding from certain investors, which is in line with recognizing patents as a signal. However, the paper suggests that examiners at the patent office suffer from cognitive biases. Some examiners are lenient, while others are not, and whether one receives a patent grant depends on the examiner's leniency (Farre-Mensa et al., 2020). These cognitive limitations at the patent office are outside the scope of this thesis and limit our research.

In summary, signaling through patents resolves the issues of asymmetric information between entrepreneurs and investors. Regarding venture capital funding, a startup's patenting activity has been shown to work as a signal in increasing the likelihood of attracting financing, startup valuation estimates, and the amount raised. However, the literature on patents' attractiveness across types of startup funding is scarce. Thus, to our knowledge, by studying whether patenting activities attract higher amounts of startup capital across funding types in Sweden in isolation, our thesis contributes to an existing gap in the entrepreneurial finance literature.

3. Data

This section presents our data collection process. First, we elaborate on the collection of the startup data. Subsequently, we describe the collection process of the patent dataset. Further, we explain how we matched the data. Finally, we introduce Propensity Score Matching (PSM) to construct our final sample, which will be used for further analysis.

3.1 Startup Data

To collect a sample of Swedish startups, we have assembled data from Crunchbase. Crunchbase is a website that provides firm and funding-specific information. The platform allows members to retrieve data on startup companies, investors, transactions, among others, listed in the database (Crunchbase Inc, n.d.-a).

Table 1: Summary of the steps in the sample collection process

Steps	Sample selection process	Startups
1	For-profit Swedish startups founded between 1990 and 2007	3,749
2	Remove startups with missing data on the total funding amount	351
3	Remove startups with missing data on the first funding round	323
4	Remove startups with post-IPO or unknown funding rounds	302
5	Remove startups with more than 400 employees	293

We have gathered information on for-profit startups with headquarters in Sweden founded between 1990[1] and 2007. To avoid the possible damaging effects of the 2008 financial crisis, we start our data collection with startups founded in 2007 and work our way back. The entire and raw dataset includes 3,749 Swedish startups.

We remove startups that have received funding after the Initial Public Offering (IPO). The reason is that we want to study startups before their IPO. We also remove startups with more than 400 employees. It is challenging to set a clear cut on the number of employees a firm can have before ceasing to be considered a startup. Crunchbase does not provide the number of employees working at a startup at the time of each funding round, and we thereby assume this number to be accumulated. However, for the startups that received their first-round funding

[1] The explanation for why we stop at 1990 is provided in section 3.2.

several years ago, we expect the number of employees to be well below what Crunchbase reports at the time of that funding round. Zhou et al. (2016) examine startups with less than 100 employees in their study. In our opinion, 100 is too low considering that we deal with accumulated numbers, and we choose to exclude startups with more than 400 employees instead. After completing our sample collection process summarized in Table 1, we are left with 293 startups with complete data on the amount of funding raised in the first round.

3.2 Patent Data

We use Google Patents[2] to retrieve data on granted patent applications (Google, n.d.). When searching Crunchbase for startups, we start in 2007 and collect all startups founded that year. Simultaneously, we manually search the startups with complete funding data founded in 2007 in Google Patents to see how many have filed a patent application. For each year, we continue this process, working our way backward. We stop at 1990 as approximately one-third of the 293 startups filed and were granted a patent through the USPTO during 1990-2020, which we consider a sufficiently large portion to conduct our study. In total, the startups in our sample filed and were granted 524 patent applications during the respective period.

Even though we limit our thesis to patent applications, we collect data on granted patents to ensure the application date is published.[3]

3.3 Matching Startup and Patent Data

Employing software, we match the patent data with the Crunchbase sample on the name of the startup. Crunchbase does not report the company's full legal name for some startups; e.g., the Swedish term "AB" is sometimes missing. Therefore, before matching, we remove such abbreviations and hence increase our matching opportunities. The matching procedure leaves us with 85 startups that filed and were granted at least one patent in 1990-2020.

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[2] We choose to use Google Patents to collect data on granted patent applications as this database is convenient to use.

[3] Before 29 November, 2000 the USPTO did not publish patent applications that were not granted (Marco, Carley, Jackson, & Myers, 2015).

3.4 Propensity Score Matching

At this point, we can divide our sample into two groups: those who have filed a patent application and those who have not. We must bear in mind that there might be several characteristics other than the patent application that distinguishes the two groups. Ideally, we want the patenting startups to have the same characteristics as the non-patenting startups. The only difference between the groups should be whether or not they have filed a patent. That is, for each patenting startup, we want a non-patenting startup to be as similar as possible on all observable characteristics. In order to do this, we apply PSM (Austin, 2011), which is described in detail in the section below.

3.4.1 Treatment and Control Group

We refer to the patenting startups as the treatment group. For each startup in the treatment group, we want to select one non-patenting startup. These non-patenting startups will eventually form our control group. We want each pair to be as identical as possible. However, it is practically impossible to find completely identical startups where one has filed a patent application while the twin has not (Austin, 2011). Thus, we make the best possible match based on all available information and reduce selection bias by applying PSM.

PSM was first introduced by Rosenbaum and Rubin (1983), and the authors defined it as "the conditional probability of assignment to a particular treatment given a vector of observed covariates" (p. 41). The propensity score for treatment is denoted

$$e(x) = pr\ (z = 1 \mid x) \tag{1}$$

Where z = 1 indicates treatment, and x is the observed covariates. *E(x)* is the probability of being treated (Rosenbaum & Rubin, 1983). When applying the propensity score for matching purposes, the procedure employs the covariates representing observable pre-treatment characteristics and tries to find comparable control objects to the treated based on these characteristics (Caliendo & Kopeinig, 2008; Rosenbaum & Rubin, 1983).

In order to estimate the propensity score for each startup, we run a logistic regression model (Austin, 2011). In logistic regression, the dependent variable can take one of two values, in our case indicating 1 if the startup has filed a patent application before the first funding round and 0 otherwise. The treatment group in our case consists of 66 startups, i.e., out of the 85 startups that had ever filed a patent application, 66 of these did so before the first funding round. The independent variables are the covariates representing pre-treatment characteristics (Guido, Winters, & Rains, 2006). The covariates implemented in our model are the industry the startup operates in, the startup's foundation year, and whether or not the startup is located in Stockholm. All these covariates are dummy variables.

We choose industry as one of the covariates because we believe some industries are more likely to file a patent application than others. Further, by including the foundation year, the treatment and control startups are assumed to have had the same point of departure for success or failure. When founded approximately the same year, they are expected to follow the same policies and operate in the same economic surroundings. Regarding the location of the matched startups, we argue that startups located in Stockholm are more likely to benefit from the same positive spillover effects than startups located elsewhere, in the early stages (Almeida, Dokko, & Rosenkopf, 2003). Such spill-over effects can be sharing of knowledge or learning from successful startups located in the area.

We apply the nearest neighbor method to match treated startups with untreated startups. We specify the model to start with the treated startups with the highest propensity score and then find an untreated startup with the closest propensity score to the treated one. In addition, we use 1:1 matching, i.e., for each treated startup, only one untreated startup is selected as a control unit. Further, we specify the model to match without replacement of the untreated startups. Without replacement means that each untreated startup can only be paired once to a treated subject. The untreated startups that have been matched form our control group (Austin, 2011). The PSM leaves us with 66 control startups, 132 startups in total.

Table 2 presents the covariate balance between the treated and the untreated group before applying PSM. Columns 3 and 4 show the occurrence of untreated and treated units for each level of the dummy variables, and occurrence in percentage terms is included in parenthesis.

There are significant differences between the two groups for the covariates *Capital* and *Industry*, which we can tell from the resulting low p-values[4]. Though p-values have to be used with caution in these types of analysis since a higher p-value after matching can be a result of the decreased sample size. Another method to measure covariate balance between the two

[4] The p-values are obtained by a chi-square test (Howarter, 2015).

groups, commonly used in PSM analysis, is by calculating the standardized mean difference (SMD)[5] for each covariate (Howarter, 2015). According to Austin (2011), an SMD value of less than 0.1 indicates covariate balance between the two groups for a particular covariate. As can be seen from Table 2, the SMD exceeds the threshold of 0.1 for all covariates. Therefore, we can conclude there exist covariate imbalance between the two groups before performing our matching procedure.

Table 2: Covariate balance between the untreated and treated group before PSM

	Level	Untreated	Treated	p-value	SMD
Number of observations		227	66		
Capital (%)	No	129 (56.8)	54 (81.8)	<0.001	0.563
	Yes	98 (43.2)	12 (18.2)		
Industry (%)	Administrative Services	3 (1.3)	1 (1.5)	0.001	1.335
	Advertising	7 (3.1)	1 (1.5)		
	Agriculture and Farming	0 (0.0)	2 (3.0)		
	Apps	6 (2.6)	0 (0.0)		
	Artificial Intelligence	5 (2.2)	0 (0.0)		
	Biotechnology	18 (7.9)	22 (33.3)		
	Clothing and Apparel	3 (1.3)	0 (0.0)		
	Commerce and Shopping	17 (7.5)	0 (0.0)		
	Community and Lifestyle	2 (0.9)	1 (1.5)		
	Consumer Electronics	19 (8.4)	6 (9.1)		
	Consumer Goods	1 (0.4)	0 (0.0)		
	Content and Publishing	9 (4.0)	0 (0.0)		
	Data and Analytics	10 (4.4)	2 (3.0)		
	Design	4 (1.8)	1 (1.5)		
	Education	3 (1.3)	0 (0.0)		
	Energy	7 (3.1)	5 (7.6)		
	Financial Services	6 (2.6)	1 (1.5)		
	Food and Beverage	4 (1.8)	0 (0.0)		
	Gaming	5 (2.2)	0 (0.0)		
	Hardware	18 (7.9)	10 (15.2)		
	Health Care	11 (4.8)	4 (6.1)		
	Information Technology	26 (11.5)	3 (4.5)		
	Internet Services	4 (1.8)	0 (0.0)		
	Manufacturing	13 (5.7)	3 (4.5)		
	Media and Entertainment	6 (2.6)	0 (0.0)		

[5] The formula to calculate SMD is provided in Appendix B.

	Mobile	1 (0.4)	0 (0.0)		
	Other	5 (2.2)	2 (3.0)		
	Professional Services	4 (1.8)	1 (1.5)		
	Sales and Marketing	1 (0.4)	0 (0.0)		
	Science and Engineering	0 (0.0)	1 (1.5)		
	Software	6 (2.6)	0 (0.0)		
	Sports	1 (0.4)	0 (0.0)		
	Sustainability	1 (0.4)	0 (0.0)		
	Transportation	1 (0.4)	0 (0.0)		
Founded Year (%)	1990	2 (0.9)	0 (0.0)	0.513	0.591
	1991	4 (1.8)	1 (1.5)		
	1992	5 (2.2)	0 (0.0)		
	1993	2 (0.9)	0 (0.0)		
	1994	3 (1.3)	1 (1.5)		
	1995	1 (0.4)	2 (3.0)		
	1996	4 (1.8)	1 (1.5)		
	1997	5 (2.2)	0 (0.0)		
	1998	9 (4.0)	6 (9.1)		
	1999	12 (5.3)	5 (7.6)		
	2000	17 (7.5)	9 (13.6)		
	2001	19 (8.4)	8 (12.1)		
	2002	12 (5.3)	3 (4.5)		
	2003	23 (10.1)	3 (4.5)		
	2004	24 (10.6)	5 (7.6)		
	2005	25 (11.0)	6 (9.1)		
	2006	32 (14.1)	8 (12.1)		
	2007	28 (12.3)	8 (12.1)		

Table 3 reports the covariate distribution between the two groups after applying PSM. As mentioned previously, the untreated startup that is matched to a treated startup is denoted as a control unit. As can be seen from Table 3, all covariates have a lower SMD than before PSM. However, none of the covariates have an SMD below the 0.1 threshold, i.e., there is still covariate imbalance between the two groups. Even though we have not achieved full balance among our covariates, the SMD value has been reduced to a great extent for the covariates *Capital* and *Industry*. We observe that the SMD value for the *Capital* covariate is fairly close to fulfilling the criteria for balance.

Our somewhat poor matching results might be due to our small sample size. With small samples, it gets more challenging to find an optimal match (Zhao et al., 2021). We acknowledge that the matching procedure has not given us a perfect result, but we have managed to reduce the difference between the two groups. Ideally, we would include more covariates in our model, but we try to perform the best possible matching with the available information at our hand. Thus, we proceed with the matched sample for further analysis.

Table 3: Covariate balance between treatment and control group after PSM

	Level	Control	Treated	p-value	SMD
Number of observations		66	66		
Capital (%)	No	51 (77.3)	54 (81.8)	0.666	0.113
	Yes	15 (22.7)	12 (18.2)		
Industry (%)	Administrative Services	1 (1.5)	1 (1.5)	0.965	0.487
	Advertising	1 (1.5)	1 (1.5)		
	Agriculture and Farming	0 (0.0)	2 (3.0)		
	Biotechnology	18 (27.3)	22 (33.3)		
	Community and Lifestyle	1 (1.5)	1 (1.5)		
	Consumer Electronics	10 (15.2)	6 (9.1)		
	Data and Analytics	3 (4.5)	2 (3.0)		
	Design	1 (1.5)	1 (1.5)		
	Energy	5 (7.6)	5 (7.6)		
	Financial Services	0 (0.0)	1 (1.5)		
	Hardware	14 (21.2)	10 (15.2)		
	Health Care	5 (7.6)	4 (6.1)		
	Information Technology	1 (1.5)	3 (4.5)		
	Manufacturing	3 (4.5)	3 (4.5)		
	Other	2 (3.0)	2 (3.0)		
	Professional Services	1 (1.5)	1 (1.5)		
	Science and Engineering	0 (0.0)	1 (1.5)		
Founded Year (%)	1991	3 (4.5)	1 (1.5)	0.938	0.445
	1994	1 (1.5)	1 (1.5)		
	1995	0 (0.0)	2 (3.0)		
	1996	1 (1.5)	1 (1.5)		
	1998	4 (6.1)	6 (9.1)		
	1999	5 (7.6)	5 (7.6)		
	2000	9 (13.6)	9 (13.6)		
	2001	6 (9.1)	8 (12.1)		
	2002	6 (9.1)	3 (4.5)		
	2003	1 (1.5)	3 (4.5)		
	2004	5 (7.6)	5 (7.6)		
	2005	5 (7.6)	6 (9.1)		
	2006	10 (15.2)	8 (12.1)		
	2007	10 (15.2)	8 (12.1)		

3.4.2 Final Sample

To test our hypotheses, we rely on data about the first funding round for each startup. Thus, we filter the data to contain the first funding round for each startup in the sample, leaving us with 132 funding rounds. Table 4 presents descriptive statistics of our final sample. Explanations of the variables presented in the table are provided in section 4.2.

From Table 4, we can see that the average first-round funding amount for the matched sample is 5.976 million USD. We observe that there is a large gap between the minimum and maximum values for this variable. The average time from foundation to first-round funding, which can be read from the *FirmAge* variable, is approximately 9 years. The standard deviation for this variable is 6.177 years, i.e., there is a good spread. Of course, we do not know the exact reasons why it takes more time for some startups than others to raise money, but we can assume on a general basis that it is difficult for startups in the first place to receive startup funding.

Further, from Table 4, we see that the highest number of filed patent applications before the first funding round is 13. Additionally, the most common funding type in the first funding round is VC[6]. About 75% of our sample received this funding type. Further, the most represented industry is biotechnology, where 22 out of 40 startups in the biotechnology industry come from the treatment group. This is not surprising as patents serve an important role for startups in the biotechnology industry (Raidt, n.d.). Next, we observe a decent spread in which years the transactions took place, and most first-round transactions in our sample occurred in 2017.

Regarding the foundation year of the startups, there is an increasing number of founded startups throughout the years in our dataset, which might be due to improvements in data availability from Crunchbase in later years. Another observation is that there were no founded startups in our sample in 1990, 1992, 1993, and 1997. Again, one reason might be poor data availability during the early years, but also because of our small sample size.

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[6] We have grouped the following funding types into the venture capital (VC) category: Seed, Series A-G, and Venture – Series Unknown. These funding types are provided by Crunchbase (Crunchbase Inc, n.d.-b). An explanation of the pooled category can be found in Appendix A.

Table 4: Descriptive statistics of sample after matching

Variables	N	Mean	St. Dev.	Median	Min	Max
Funding	132	5.976	10.224	2.144	0.046	61.466
NumEmployees	132	39.030	61.684	31	1	376
NumInvestors	132	1.553	0.952	1	1	5
FirmAge[7]	132	9.110	6.177	8.050	0.000	26.200
Capital (dummy)	132	0.205			0	1
PatentApp (dummy)	132	0.500			0	1
NumPatentApp	132	1.174	1.880	0.5	0	13
Funding Type (dummies)						
VC	98	0.742			0	1
Angel	1	0.008			0	1
Corporate Round	1	0.008			0	1
Grant	29	0.22			0	1
Private Equity	3	0.023			0	1
Industry (dummies)						
Biotechnology	40	0.303			0	1
Administrative Services	2	0.015			0	1
Advertising	2	0.015			0	1
Agriculture and Farming	2	0.015			0	1
Community and Lifestyle	2	0.015			0	1
Consumer Electronics	16	0.121			0	1
Data and Analytics	5	0.038			0	1
Design	2	0.015			0	1
Energy	10	0.076			0	1
Financial Services	1	0.008			0	1
Hardware	24	0.182			0	1
Health Care	9	0.068			0	1
Information Technology	4	0.03			0	1
Manufacturing	6	0.045			0	1
Other	4	0.03			0	1
Professional Services	2	0.015			0	1
Science and Engineering	1	0.008			0	1
Investment Year (dummies)						
2000	4	0.03			0	1
2001	3	0.023			0	1

[7] We are aware that some startups might be too old to be considered a startup, which might provide us with a limitation. A further discussion is provided in section 7.1.

2002	1	0.008	0	1
2003	6	0.045	0	1
2004	1	0.008	0	1
2005	10	0.076	0	1
2006	12	0.091	0	1
2007	8	0.061	0	1
2008	10	0.076	0	1
2009	3	0.023	0	1
2010	9	0.068	0	1
2011	4	0.03	0	1
2012	1	0.008	0	1
2013	6	0.045	0	1
2014	6	0.045	0	1
2015	11	0.083	0	1
2016	11	0.083	0	1
2017	13	0.098	0	1
2018	4	0.03	0	1
2019	9	0.068	0	1
Founded Year				
1991	4	0.03		
1994	2	0.015		
1995	2	0.015		
1996	2	0.015		
1998	10	0.076		
1999	10	0.076		
2000	18	0.136		
2001	14	0.106		
2002	9	0.068		
2003	4	0.03		
2004	10	0.076		
2005	11	0.083		
2006	18	0.136		
2007	18	0.136		

4. Methodology and Variable Description

4.1 Methodology

To test whether the amount of startup funding is affected by a patent application for startups in Sweden before the first round, we run a simple and a multiple linear regression model.[8] The general notation of the multiple regression model is as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k + u \quad (2)$$

Where y is the dependent variable and x_i are the independent variables. Since several factors can affect the amount of funding a startup receives, other than patents, the model allows us to control for those. The forthcoming sections describe our implemented variables. An elaboration on the assumptions of the model is provided in Appendix C.

4.2 Variables

4.2.1 Dependent Variable

Our dependent variable, *ln(Funding)*, is the natural logarithm of the first-round funding amount in million USD. We apply the natural logarithm to correct for highly skewed funding amounts and normalize the variable (Wooldridge, 2020). In addition, since our data consists of funding amounts across time, we adjust for inflation. Using inflation data for Sweden provided by the World Bank (The World Bank, 2021), we adjust all funding amounts into 2010-dollars[9]. The adjustment enables us to make an apple-to-apple comparison of monetary values across time.

4.2.2 Independent Variables

Our main independent variables are *PatentApp* and *NumPatentApp*. The variable *PatentApp* is a dummy variable indicating 1 if the startup filed at least one patent application before the

[8] We only provide an explanation of the multiple linear regression model, as the simple regression model is similar, but only includes one independent variable.

[9] We adjust all funding amounts into 2010-dollars as 2010 is approximately the investment year in the middle of our sample.

first round of funding and 0 otherwise. The variable *NumPatentApp* is the number of filed patent applications by a startup before the first funding round.

4.2.3 Control Variables

Several factors can affect the amount of first-round funding a startup receives other than filed patent applications. We control for such factors by including several control variables in our regression models. Due to unavailable data on some variables for some observations, we make a few assumptions described below. We implement several control variables as in the study of Zhou et al. (2016).

We create the variable *FirmAge*, which measures the time from the foundation date of a startup to the first funding round. There might be differences in the funding amount raised among startups affected by the age of the startup. Including this control variable enables us to hold the age of a startup in our regression models fixed.

The *NumInvestors* variable indicates how many investors participated in the first funding round. This variable controls for the effect of multiple investors who take part in the first funding round. For some of the startups in our sample, there is missing information on this variable. We assume that there has to be at least one investor participating in the funding round; thus, we replace the missing values by 1.

The variable *ln(NumEmployees)* is the natural logarithm of employees working at the startup, a firm size measure. When retrieved from Crunchbase, the information on the number of employees is not complete. We assume that at least the founder is working at the startup, and thus for missing values, we set the number of employees equal to 1. Further, Crunchbase provides the number of employees as an interval, e.g., 11-50. We select the median value as the number of employees for each respective interval for each startup. We apply the natural logarithm since the data is quite spread out, with 1 as the minimum and 376 as the maximum number of employees in our sample.

Since there is a large spread in the timing of funding rounds, namely 20 years, we control for macro-economic events by including *investment year dummies*. In addition, since it is reasonable to believe that different industries receive different amounts of funding, and Zhou et al. (2016) finds that differences in funding amounts across industries are significant, we have included *industry dummies*. Lastly, considering that different types of investors typically provide different amounts of funding, and our sample consists of various funding types, we include *funding type dummies*.

5. Empirical Analysis and Results

In Table 5, we present the results of whether filing at least one patent application positively affects the first-round funding amount a startup receives, i.e., we test Hypothesis 1. The regressions are performed on the first funding round for the 132 matched startups. The primary independent variable of interest is the dummy variable *PatentApp*.

Model 1 in Table 5 is our baseline model and estimates the treatment effect. In this model, we only include the *PatentApp* dummy as our independent variable. From our result, we see that the effect of filing at least one patent application before first-round funding is positively associated with the amount of funding raised. However, the result is not statistically significant. As noted previously, we did not achieve full balance on the covariates from the PSM analysis, and this has most likely made an impact on the estimated treatment effect (Greifer, 2020).

Model 2, in Table 5, includes all control variables described in section 4.1. The *PatentApp* dummy has a positive effect on the first-round funding amount and is significant at the 10% level, supporting Hypothesis 1. Startups that have filed at least one patent application before the first funding round receive 54.3%[10] more in first-round funding than those who have not filed a patent application, holding other factors fixed. The result implies that patents come with the economic benefit of attracting more funding across funding types. The positive and significant effect is in line with previous research, especially regarding patents' effect on venture capital funding. Zhou et al. (2016) also find that filing at least one patent application before first-round funding has a positive and significant effect on the amount of venture capital raised.

The *Capital* dummy variable is positive in sign and significant at a 10% level. This result suggests that being located in Stockholm has a positive effect on startup funding. In our opinion, it seems reasonable to argue that startups located in Stockholm benefit from spillover effects from successful startups. The variables *NumInvestors* and *ln(NumEmployees)* are commented on at the end of this section.

[10] Since our dependent variable is ln(y), we provide a more precise estimate as follows: 100*[exp(0.434) – 1] = 54.3% (Wooldridge, 2020).

Table 5: Filing a patent application before the first funding round

The ordinary least squares regressions estimate the effect of filing a patent application on the first-round funding amount a startup receives. Our main independent variable of interest *PatentApp* is a dummy, equal to 1 if the startup filed at least one patent application before the first funding round, and 0 otherwise. Base group for investment year: 2000; base group for industry: biotechnology; base group for funding type: VC. Standard errors are reported in parenthesis below the coefficients.[11] Statistical significance is reported with *, **, *** indicating significance at a 10%, 5%, and 1% level, respectively.

	Dependent variable:	
	ln(Funding)	
	(1)	(2)
PatentApp	0.298	0.434*
	(0.335)	(0.252)
FirmAge		0.014
		(0.038)
NumInvestors		0.576***
		(0.163)
Capital		0.574*
		(0.334)
ln(NumEmployees)		0.215**
		(0.105)
Investment year dummy	No	Yes
Industry dummy	No	Yes
Funding type dummy	No	Yes
Observations	132	132
R^2	0.006	0.704

Table 6, below, shows the results of whether the number of patent applications filed positively affects the first-round funding amount a startup receives, i.e., we test Hypothesis 2. Also, this regression is performed on the first funding round for the 132 matched startups. In this analysis, the main independent variable of interest is *NumPatentApp*.

[11] We perform the Breusch-Pagan test for heteroskedasticity on the two models (Breusch & Pagan, 1979). For both models, the p-value is sufficiently large enough to fail to reject the null hypothesis of homoskedasticity (Wooldridge, 2020).

Again, model 1 is the baseline model. The *NumPatentApp* coefficient is significant at the 1% level. The result suggests that the number of patents before the first round of funding significantly positively affects the startup funding amount.

In model 2, we apply all control variables from section 4.2.3. *NumPatentApp* has a positive effect on the first-round funding amount and is significant at the 5% level. A one standard deviation increase in *NumPatentApp* increases the first-round funding a startup receives by 14.9%[12] compared to its mean. The result suggests that if a startup holds more than one patentable innovation, it should apply for patents to raise more startup funding. Our results are in line with Hoenen et al. (2014), who found that an increase in the number of patents filed was positively associated with the higher amounts of venture capital funding.

Table 6: Number of filed patent applications before the first funding round

The ordinary least squares regressions estimate the effect of the number of filed patent applications on the first-round funding amount a startup receives. Our main independent variable of interest *NumPatentApp*, is the number of filed patent applications before the first round of funding. Base group for investment year: 2000; base group for industry: biotechnology; base group for funding type: VC. Standard errors are reported in parenthesis below the coefficients.[13] Statistical significance is reported with *, **, *** indicating significance at a 10%, 5%, and 1% level, respectively.

	Dependent variable:	
	ln(Funding)	
	(1)	(2)
NumPatentApp	0.237***	0.142**
	(0.065)	(0.067)
FirmAge		0.004
		(0.038)
NumInvestors		0.542***
		(0.163)
Capital		0.528
		(0.331)
ln(NumEmployees)		0.204*
		(0.105)

[12] *NumPatentApp* coefficient = 0.142. Standard deviation of *NumPatentApp* variable = 1.880. Mean value of the dependent variable *Funding* = 5.976. Calculations: (0.142*1.880) / ln(5.976) = 0.149

[13] As in Table 5, we perform the Breusch-Pagan test for heteroskedasticity (Breusch & Pagan, 1979). Applying a significance level of 10%, we reject the null hypothesis of homoskedasticity for model (1). Because of that, we report heteroskedasticity-robust standard errors (White, 1980) for this model.

Investment year dummy	No	Yes
Industry dummy	No	Yes
Funding type dummy	No	Yes
Observations	132	132
R^2	0.054	0.709

In both Table 5 and Table 6, the variable *NumInvestors* positively affects first-round funding and is significant at the 1% level. The *NumInvestors* variable tells us that the more investors participating in the first round, the more funding the startup will raise, holding other factors fixed. Additionally, from Table 5 and Table 6, we see that the variable *ln(NumEmployees)* positively affects the first-round funding a startup receives, and is statistically significant at the 5% level and 10% level, respectively. The variable *ln(NumEmployees)* is a measure of firm size, and from our results, we can see that sizeable startups attract more in first-round funding, holding other factors fixed.

6. Discussion

The analyses demonstrate a positive correlation between patent applications and startup funding for Swedish startups. In line with our first hypothesis, the effect of having filed at least one patent application before the first round of startup funding increases the amount by 54.3%. The result, in line with the signaling theory of Spence (1973), suggests that the IP-right communicates valuable information regarding startup characteristics to investors that can be challenging to identify.

Even though the literature on patents with regard to startup funding across funding types is scarce, our findings align with previous empirical findings. Previous research provides evidence that patenting activity assist startups in attracting venture capital funding and thus increases the funds raised (Baum & Silverman, 2004; Cockburn & MacGarvie, 2009; Conti et al., 2013; Farre-Mensa et al., 2020; Mann & Sager, 2007; Zhou et al., 2016). Our analysis provides a similar result; however, we find that the same is true for Swedish startups across funding types.

From the startup's perspective, by applying for a patent and thereby reliably communicating its qualities, startups gain an advantage to raise more considerable amounts of funding in their first funding round. More capital provides opportunities to achieving certain milestones, a greater probability of successful development, and ultimately startup survival.

Especially in the case of Swedish startups, these findings are highly relevant. Due to the nature of the debt issuance system in Sweden, the person in charge of a company that goes bankrupt is held personally accountable. He or she is at risk of being haunted by bad credit ratings for the rest of their life (Knowledge@Wharton, 2015). This constraints people as they become more risk-averse and less willing to take out loans and eventually to found startups. Our results imply that by applying for patents, the startup has an excellent opportunity to benefit from equity investments and thus can avoid taking on expensive debt that might go at the expense of the entrepreneur's personal finance if the startup fails. Additionally, with this in mind, our results suggest that entrepreneurship activity in Sweden can stay at a high level, as entrepreneurs can stay somewhat risk-loving.

From an investor's perspective, our results suggest that patents increase the valuation estimates of a startup, making investors willing to provide more funding in the first round. This is in line with previous findings in that patent activity seems to increase venture capitalists' estimates of startup value (Hsu & Ziedonis, 2008), especially in early financing rounds (Hsu & Ziedonis, 2013), and thus increases the amounts of venture capital funding.

However, our results contradict the claims of Conti et al. (2013) and Sudek (2007). Our analysis suggests that patent applications constitute an adequate signal for venture capitalists as well as other types of funding, such as angels. The contradicting result might be due to the country in question. It might be that patents are not evaluated to be a valuable signal of desirable startup characteristics in the US but are in Sweden. Since Sweden has a lot of startup activity, patent applications might be an instrument to differentiate low-quality startups from high-quality startups without much effort. However, another reason for the contradicting results might be that the various investors in our sample consider patents valuable, while on a general basis, at least angels do not consider the IP-right important.

Nevertheless, going through with the application process is a cost-benefit analysis. Startups should only go through with the application as long as the benefit, i.e., the amount of funding, outweighs the cost of applying. As long as the startup has an invention that can be patented, and the startup believes the quality of their invention is high, or prospects are significant, our results indicate that startups will benefit significantly from applying for a patent before turning to investors for funding.

Our second analysis addresses whether the patent application stock has a positive effect on first-round startup funding and supports our second hypothesis. The results from Table 6, after some minor calculations, suggest that a one standard deviation increase in the number of patent applications is associated with an increase in first-round funding of 14.9%, compared to its mean. This result suggests that investors provide larger funding amounts when innovation productivity is high.

The analysis complements previous findings, which provide evidence that the patent applications count positively significantly affects venture capital funding amounts (Baum & Silverman, 2004; Hoenen et al., 2014). On the contrary, our results indicate that the same is true across funding types for Swedish startups.

In other words, the more patents a startup applies for signals, among other things, innovative activity, making investors better informed about the startup and providing more funding in the first round. Thus, one can argue that increasing the application stock before seeking external funding increases the probability of startup survival.

Our results suggest that investors value innovative activity, among other things, in startups, as patents assist startups in increasing the amount raised in the first funding round. However, it might be that investors do not necessarily value the innovation activity by itself, but rather the right patents give to exclude competitors and thus secure larger profits in the future.

Overall, our findings suggest that patent applications are associated with higher first-round funding across funding types for Swedish startups. The size of the economic impact of patents in both analyses is somewhat surprising. It is similar to the ones reported for venture capital funding amounts in the research mentioned above. The similarity in size is interesting since venture capitalists rarely make one-time upfront investments but rather stage their investment amounts (Gompers & Lerner, 2001). Therefore, one could argue that the size of economic impact should be larger across funding types since some startup investors do not stage their investments. On the other hand, the similarity in effect sizes might confirm that patents serve the same signaling purpose across funding types as it does for venture capitalists.

7. Limitations and Further Research

We acknowledge that our thesis is subject to some limitations, especially regarding our data collection. This section describes these limitations. Additionally, we provide suggestions for further research.

7.1 Limitations

First and foremost, our sample of startups is dated approximately 30 years back in time. One can thereby argue that some of the companies in our sample can no longer be considered a startup. Even though there is no clear cut on when a company ceases to be in the startup phase, the firm size and age indicate that some might have developed past this stage. Some of the startups in our sample have grown so large and “old” that they might not be considered a startup.

Our sample of startups was founded from and before 2007 and limits us regarding data on control variables to implement in our analysis. Crunchbase was founded in 2007, and even though we consider the data reliable, as it comes from Crunchbase’s venture partners, we have not been able to extract a desirable amount of startup and investor characteristics. Thus, one cannot rule out the possibility that our results can be explained by other financing drivers that have not been considered due to unavailable data.

Even though the covariates used as matching criteria in the PSM should provide us with startups with similar pre-treatment characteristics, this is not the case for all startups. It might be that our sample of 293 startups is not sufficiently large for the PSM model to find perfect matches based on the three covariates. However, as each startup is unique in one way or another, the probability of finding two perfectly equal startups is very challenging. Thus, our somewhat poor matching results might cause a limitation.

7.2 Suggestions for Further Research

To correct for the limitations provided by this thesis, as a suggestion for further research, we propose applying a dataset of newly founded startups in Sweden. It is reasonable to believe that the information on startup and investment characteristics will be both available and up to date, supplying additional controls that can affect the funding amount.

Further, a qualitative study of our hypotheses, including both startups and investors, would be interesting to see whether the empirical results align with the qualitative. Moreover, a deeper understanding of what drives the economic impact of patents might be discovered.

Additionally, during our work, we have discovered that in Sweden, trademarks are filed more frequently compared to patents (World Intellectual Property Organization, 2021). Thus, it would be interesting to investigate whether trademarks provide even more significant startup funding amounts than do patents.

8. Conclusion

Throughout this thesis, we have examined whether patents positively affect Swedish startups seeking startup funding. We try to answer whether having filed at least one patent application before the first funding round increases the amount of funding a startup receives. Additionally, we try to answer whether the amount of startup funding also increases with the number of filed patent applications. Our empirical analyses suggest that the amount of first-round funding for Swedish startups increases if the startup have filed at least one patent application, in line with Hypothesis 1. Additionally, the number of filed patent applications before funding also positively affects the first-round funding, supporting Hypothesis 2. Thus, our findings imply that patents constitute an effective signal that reduces information asymmetries and assists startups in attracting startup funding.

There is a common understanding that patenting startups are more likely to be successful, both in the literature and public space. A possible explanation is that patents are publicly available documents that reduce information asymmetries regarding startup characteristics challenging to assess. Thus, one can argue that patents serve the purpose of a signal.

Previous research has investigated whether patenting activity attracts higher amounts of venture capital funding, with great success. Most studies find a positive association of patents regarding the probability of attracting financing and the amounts of funds raised. The few studies that take into account other types of funding, such as angels, are contradicting. We were motivated by this gap in the literature; as to our knowledge, no studies have ever been conducted across funding types nor in a Nordic country in isolation.

Investigating a sample of 132 startups in Sweden, the results from our analyses indicate that besides legal protection, patents serve a signaling purpose that attracts investors across funding types. These results can have significant implications for upcoming entrepreneurs in Sweden. Thus, startups with patentable inventions should go through with the application process to attract external investors and thus increase the probability of future success.

Our results suggest that patents provide startups with economic benefits in terms of increased first-round startup funding and should be considered valuable to Swedish startups.

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Appendix

Appendix A: Definition of Funding Types

Here we provide a description of the various funding types found in our sample, based on the explanations in the *Glossary of Funding Types*, by (Crunchbase Inc, n.d.-b).

We have pooled some funding types into the VC category. The funding types within this category includes Seed funding, Series A-G, and Venture – series unknown. The amount raised varies from 10k-20M USD in a seed round to 10M+ USD in later rounds, such as series C-G. However, there is no limit on how much funding a startup can raise in each round, these are just approximations of what is usually raised (Crunchbase Inc, n.d.-b).

The remaining funding types in our sample is angel, corporate round, grant and private equity. Angel rounds is typically one of the first rounds a startup receives, and the amount is not of significant size. In a Corporate Round, there is a company acting as a venture capitalist, investing in the startup. Grant funding is characterized by investors donating capital, without getting anything in return, such as equity stakes. Finally, Private Equity is provided to more mature startups and usually amounts to approximately 50M USD (Crunchbase Inc, n.d.-b).

Appendix B: Propensity Score Matching

B1 Standardized mean difference (SMD)

Down below is the formula for calculating the SMD for binary variables. $\hat{p}_1$ is the occurrence of the binary variable in the treatment group, and $\hat{p}_2$ is the occurrence of the binary variable in the control group (Zhao et al., 2021).

$$SMD = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{[\hat{p}_1\,(1 - \hat{p}_1) + \hat{p}_2\,(1 - \hat{p}_2)]/2}} \tag{3}$$

Appendix C: Econometric Model

When applying a multiple linear regression model, one tries to estimate the linear relationship between a dependent and multiple independent variables. The relationship is estimated through an ordinary least squares (OLS) method. The method aims to reduce the sum of squares in the distance from the true value and the estimates of the dependent variable, as much as possible, and thus provide an unbiased estimate of the population (Wooldridge, 2020). For the OLS to be the best linear unbiased estimators, five Gauss-Markov assumptions need to hold. One additional assumption should be in place for the estimators to also be efficient, as explained in Wooldridge (2020):

1. The parameters of the population must be linear (Wooldridge, 2020):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + u \tag{4}$$

2. The data applied in the model is a random sample of *n* observations from the population (Wooldridge, 2020):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + u, \qquad where\ i = 1, 2, \ldots, n \tag{5}$$

3. Both in the sample and the population, there must be variation in the values of the independent variables. Additionally, the independent variables cannot be perfectly correlated (Wooldridge, 2020).
4. Given any values of the independent variables, the value of the expression for unobservable factors that affects *y*, the error term *u*, is expected to be 0 (Wooldridge, 2020):

$$E(u|x_1, x_2, \ldots, x_k) = 0 \tag{6}$$

5. Homoskedasticity, i.e., conditional on any value of the independent variables, the error term *u* has the same variance. In case of violation, there is heteroskedasticity in the *u* term (Wooldridge, 2020):

$$Var(u|x_1, x_2, \ldots, x_k) = \sigma^2 \tag{7}$$

6. Normality, meaning the error term *u* of the population is identical and independent with a mean of 0 and variance of σ^2 (Wooldridge, 2020):

$$u \sim Normal(0, \sigma^2) \tag{8}$$

Under assumptions 1-6 the OLS estimators are the best linear unbiased and efficient estimators (Wooldridge, 2020).

C1 Check for multicollinearity

In order to check for multicollinearity, we calculate the variance inflation factor (VIF) for the main independent variables of interest and some of the control variables that are used in the two multiple regression models from section 5. As a rule of thumb, a VIF below 5 for a variable will not cause multicollinearity issues (Buteikis, 2020). From tables 7 and 8, we can see that we do not suffer from multicollinearity problems for these variables. However, the funding type dummy *Angel* and investment year dummy *2012* give us a multicollinearity issue. There is only one observation for each, and they appear simultaneously; therefore, they explain each other perfectly. We do not find this to be a problem as we do not observe multicollinearity issues among our main independent variables of interest (Frost, n.d.).

Table 7: Check for multicollinearity

Variables	VIF	Below 5
PatentApp	1.284	Yes
FirmAge	4.483	Yes
NumInvestors	1.929	Yes
Capital	1.471	Yes
ln(NumEmployees)	1.561	Yes

Table 8: Check for multicollinearity

Variables	VIF	Below 5
NumPatentApp	1.308	Yes
FirmAge	4.565	Yes
NumInvestors	1.959	Yes
Capital	1.466	Yes
ln(NumEmployees)	1.572	Yes

C2 Breusch-Pagan test for heteroskedasticity

Table 9 shows the results from the Breusch-Pagan test for the models in Table 5, while Table 10 shows the same test for the models in Table 6. Applying a significance level of 10%, we reject the null hypothesis of homoskedasticity for model 1 in Table 6. For the other models, we fail to reject the null hypothesis. A chi-square distribution with *k* degrees of freedom is used to obtain the p-values (Wooldridge, 2020).

Table 9: Breusch-Pagan test for heteroskedasticity

Models	LM-statistic	df	p-value
M1	0.11915	1	0.73
M2	34.515	43	0.8186

Table 10: Breusch-Pagan test for heteroskedasticity

Models	LM-statistic	df	p-value
M1	2.9747	1	0.08458
M2	37.563	43	0.7055

Appendix D: Descriptive Statistics of Full Sample

Table 11: Descriptive statistics of full sample (293 startups)

Variables	N	Mean	St. Dev.	Median	Min	Max
Funding	293	5.886	13.272	2.084	0.005	156.864
NumEmployees	293	54.635	84.109	31	1	376
NumInvestors	293	1.464	0.813	1	1	5
FirmAge	293	9.223	6.494	8.100	0.000	28.800
Capital	293	0.375	0.485	0	0	1
Funding Type	N	Mean				
Angel	7	0.024				
Convertible Note	3	0.01				
Corporate Round	3	0.01				
Debt Financing	1	0.003				
Equity Crowdfunding	4	0.014				
Grant	38	0.13				
Pre-Seed	1	0.003				
Private Equity	5	0.017				
Secondary Market	2	0.007				
VC	229	0.782				
Industry	N	Mean				
Administrative Services	4	0.014				
Advertising	8	0.027				
Agriculture and Farming	2	0.007				
Apps	6	0.02				
Artificial Intelligence	5	0.017				
Biotechnology	40	0.137				
Clothing and Apparel	3	0.01				
Commerce and Shopping	17	0.058				
Community and Lifestyle	3	0.01				
Consumer Electronics	25	0.085				
Consumer Goods	1	0.003				
Content and Publishing	9	0.031				
Data and Analytics	12	0.041				
Design	5	0.017				

Education	3	0.01
Energy	12	0.041
Financial Services	7	0.024
Food and Beverage	4	0.014
Gaming	5	0.017
Hardware	28	0.096
Health Care	15	0.051
Information Technology	29	0.099
Internet Services	4	0.014
Manufacturing	16	0.055
Media and Entertainment	6	0.02
Mobile	1	0.003
Other	7	0.024
Professional Services	5	0.017
Sales and Marketing	1	0.003
Science and Engineering	1	0.003
Software	6	0.02
Sports	1	0.003
Sustainability	1	0.003
Transportation	1	0.003

Investment Year	N	Mean
1999	1	0.003
2000	7	0.024
2001	4	0.014
2002	2	0.007
2003	7	0.024
2004	3	0.01
2005	17	0.058
2006	31	0.106
2007	22	0.075
2008	26	0.089
2009	9	0.031
2010	15	0.051
2011	16	0.055
2012	3	0.01
2013	11	0.038
2014	14	0.048
2015	18	0.061
2016	29	0.099
2017	24	0.082
2018	12	0.041
2019	17	0.058

2020	4	0.014
2021[14]	1	0.003
Founded Year	N	Mean
1990	2	0.007
1991	5	0.017
1992	5	0.017
1993	2	0.007
1994	4	0.014
1995	3	0.01
1996	5	0.017
1997	5	0.017
1998	15	0.051
1999	17	0.058
2000	26	0.089
2001	27	0.092
2002	15	0.051
2003	26	0.089
2004	29	0.099
2005	31	0.106
2006	40	0.137
2007	36	0.123

[14] Inflation rate for 2020 was used to adjust the monetary value back to 2010.