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Patent Registration among Swedish Firms:

Gaining an Understanding of the Relationships between firm-level Profits, Age and Patenting

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Abstract

This paper investigates the relationships between firm age, year-to-year profit-levels and patenting-levels for some of the most patent innovative Swedish firms during the period 2010-2013. With consideration to existing literature on the topic of patenting, underlying mechanics of patenting, company characteristics linked to patenting and factors specific to Sweden, two short time-series econometric models were developed. Using data gathered from the Serrano and PAtLink Databases, provided by the Swedish House of Finance via the Stockholm School of Economics, 40 companies with at least five patents registered in Sweden during the period 2010-2013 were randomly selected and analyzed. The empirical analysis showed that firm age was not a statistically significant factor in and of itself while profits were, for the number of patents registered in expectation. Implications from these results include that resources such as profits may be more important than experience in terms of years, and that firm age may only be a relevant predictor of patenting levels to the extent that it correlates with other factors. Lastly, we make some suggestions for additional areas of research related to Swedish patenting, such as proposing more extensive econometric models, and comment on the implications of these results for business and stakeholders.

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Contents

1 Introduction

What is innovation? Attempting to define such a vast and wide concept poses several challenges. That difficulty lies in part in the very nature of the term and it may further vary depending on the context in which it is used. The process of innovating can be descriptively analogous to a spark of insight that leads to further research, and it can come in different shapes in different environments.[1] Investigating and further proposing new ideas is often referred to as necessary within a global context as an answer to rising challenges affecting societies around the world. Over the last decades, new industries relying on young and innovative technologies have completely reshaped the way a variety of business sectors operate.[2] The Swedish start-up scene in particular has received much praise, and is mentioned specifically on the topic of innovation on Sweden's official website.[3] While innovation can be expressed through a variety of different ways and channels, one expression of innovation is marked by patents.[4] Patents serve an important function in how they make it possible to protect inventions and certain works from immediate competition by other firms or parties.[5] However, innovation may not always come for free and could require that firms invest in research and development. At the same time, the young companies garnering much attention do not necessarily have neither years of experience within inventing nor make a lot of money. Learning more about to what extent firm age and profitability matter for Swedish patenting becomes a particularly interesting topic of research.

2 Purpose

Sweden is frequently mentioned within the area of innovation and was ranked second in the world using data from 2019 by WIPO, the World Intellectual Property Organization.[6] Sweden is also a leader within patenting of smart technologies with the highest increase in patent applications in that area in Europe between 2012 and 2018.[7] Commenting on Sweden's success, Peter Strömbäck, General Director of the Swedish Patent and Registration Office[8], noted that there is still potential for improvement, especially for young and small and medium size companies, SMEs.[9] In many businesses, patents are of great importance when it comes to choosing whether or not to invest into research.[10] Also, literature on the topic shows that larger companies generally appear to research the most[11], which seems to be in line with Strömbäck's comment if this affects young Swedish companies' patenting. However, Swedish capital markets seem relatively active[12], relatively much is spent on research in Sweden [13], and Swedish patenting-levels seem to stand out. Considering the availability of key data on patenting in Sweden, combined with the availability of firm financial data registered to Swedish authorities, this becomes a relevant point of entry for further analysis. Young companies may not have the financial resources that larger, old companies may do in regards to research and other patent associated costs. Do profits matter for the number of patents registered? Are younger, likely smaller, companies at a disadvantage? Does age matter in the production of patentable innovation in Sweden? These questions constitute the core motivation for writing this paper.

[1] U.S. Department of Education, What Do We Mean About "Innovation"?, 12/06/2004
[2] Kost D., 6 Ways That Emerging Technologies Is Disrupting Business Strategy, Harvard Business School, 10/02/2020
[3] Swedish Institute, Innovation in Sweden, 03/05/2021
[4] Organisation for Economic Co-Operation and Development (OECD), Patents and Innovation: Trends and Policy Challenges, page: 5, 2004
[5] World Intellectual Property Organization (WIPO), Frequently Asked Questions: Patents
[6] Patent och Registreringsverket (PRV), Sverige tvåa i världen på innovation, 02/09/2020
[7] Patent och Registreringsverket (PRV), Sverige i världstoppen över innovation inom tech-området, 10/12/2020
[8] Patent och Registreringsverket (PRV), Generaldirektör och ledningsgrupp, 02/03/2021
[9] Patent och Registreringsverket (PRV), Sverige tvåa i världen på innovation, 02/09/2020
[10] Hellstadius Å., Immaterialrätt och marknadsrätt - ur praktiskt perspektiv, page: 43, 14/08/2020
[11] OECD SME and Entrepreneurship Outlook 2019, Access to innovation assets, Organisation for Economic Co-Operation and Development (OECD), chapter 7, 20/05/2019
[12] The State of European Tech, Another record breaking year for European tech, Atomico, page: 9, 04/12/2018
[13] Swedish Institute, Innovation in Sweden, 03/05/2021

The purpose of this research effort is to extend the current literature on the topic of Swedish patenting, by exploring to what extent and in what ways firm age and year-to-year profitability matter for the most patent innovative Swedish firms. Gaining a better understanding of what factors help drive the creation of patents among Swedish companies, and the possible resource constraints at play for different types of firms, could potentially help widen the discussion on the topic of innovation. Especially for the most innovative firms. Learning more about the conditions underpinning Swedish patenting, and especially regarding age and profitability, could be of value not only to the Swedish Patent and Registration Office, but to policy makers, government and firm management. This will be carried out through first presenting some current literature on the topic of Swedish and international patenting. Then, econometric models using available data will be used to analyze the relationships between firm registration year, profits and the number of patents registered for a period of years. Empirical results will then be analyzed and conclusions presented.

3 Current Literature

3.1 Patenting, its Production and some Effects

While innovation as a concept can be difficult to define in and of itself, there is legal protection for some share of Swedish innovative solutions through the patentability of unique ideas. While innovative, intangible ideas are not subject to patentability, distinct technical solutions can find legal protection if they fulfill specific legal requirements. While patents and guarding them from potential infringements can be costly[14], filing costs for a Swedish patent may be relatively low according to the Swedish Patent and Registration Office.[15] The general motivation for allowing firms to patent certain technical solutions is to provide commercial protection, in part to encourage among other things capital-intensive long-term investments into the generation of ideas.[16] The extent to which patents interact with profitability, and what underlying firm-specific conditions help stimulate patentable innovation on a firm level, is a topic that has been of interest to several researchers and discussed in applied, empirical work.

Fundamental theories within the field of economics treat the concept of innovation and its effects in different ways which may be relevant to understand patenting. The Solow model of growth views economic development through the combined effect of capital, labor and total factor productivity. The innovative aspect of total factor productivity provides value to business through the growth that it provides that cannot be explained solely from capital and labor. Unique ideas with new applications, in how they could increase efficiency and production using capital and labour as input sources, could within this context provide an explanation for economic growth. Total factor productivity, commonly referred to as $\bar{A}$, can thus provide value in the production of things all other factors equal.[17] While the Solow model is frequently used within the context of discussing macroeconomic developments, core ideas could potentially extend to a discussion of firm-economics too. In a firm-level analysis as such, this framework of thought may indicate that overall innovation and ingenuity in using existing factors plays a distinct role in separating more patent producing firms from less patent producing ones. If some firms are more productive and efficient in using their resources, this may affect their relative number of patents produced. In this way, this theory may effectively shine some light on the patent production process within firms.

However, even though patents may be the result of innovations created from the combination of capital and labour resources, the reasons why firms use patenting has been subject to some change, as brought up in a paper from the Centre for European Economic Research called “The Influence of Strategic Patenting on Companies’ Patent Portfolios”. While patenting historically has been used to shield profits from new inventions, there has been a subtle shift in trends around the 2000s. To an increasing degree, the filing of patents has also become part of competitive blocking-strategies in efforts by firms to hinder the behaviours and efforts of other firms. The authors note that “The number of patent applications increased notably faster than companies’ RD expenditures, even though companies attributed a decreased role to patents in protect-

[14] Hellstadius Å., Immaterialrätt och marknadsrätt - ur praktiskt perspektiv, page: 43, 14/08/2020
[15] Patent och Registreringsverket (PRV), Costs, 23/07/2019
[16] Hellstadius Å., Immaterialrätt och marknadsrätt - ur praktiskt perspektiv, page: 43, 14/08/2020
[17] Jones I. C., Macroeconomics, pages: 84-85, 2014

ing innovations.”. This fact shines some additional light on the process of how patents are created, and adds nuance in that the production of patents need not be a straight-forward culmination of the production of patentable ideas. Rather, patenting should be considered a complex topic subject to many different kinds of motives extending beyond the classical justification of how it protects income.[18] This can be relevant to consider when analyzing and interpreting what various coefficients truly represent in relation to the number of patents registered across companies.

Regardless of the specifics of why patents are used, there is a plethora of empirical research on the topic of patenting and its different effects, ranging from the legal efficiency to its economic implications. One conclusion that has been drawn from U.S. data is that the level of patenting is associated with some systematic effect that relates to research and development - especially on a cross-sectional level when analyzing companies on a firm level.[19] Moreover, firms that invest much capital into research tend to have a relatively high level of intangible assets, including patents, compared to material assets - indicating that financial resources spent on research may have an impact on patenting.[20] At the same time, a study using data on young start-up companies from the U.S. Patent and Trademark Office (USPTO), reveals that patents have an effect on firm profitability through for example increased revenue and innovation.[21] Connected findings are also brought up in a paper titled “The Effects of Firms’ RD Expenditures on Profitability: An Analysis with Panel Error Correction Model for Turkey” by Murat Kiraci, Ferdi Celikay and Duygu Celikay. They note that spending on research and development is associated with a robust effect on firm profitability in the long term.[22] This goes along with the overarching legal argument of why patents can be a useful type of institutional instrument, in the way that they can offer some protection of profits against losses of what is spent on research and development. When it comes to spending on research internationally, Swedish companies invest more capital into research and development compared to both the European as well as world average relative to GDP.[23]

3.2 Demographics, Tendencies and Markets

In a paper by Peter Klenow and Huiyu Li, differences in how companies contribute to overall innovation is discussed. The authors note that smaller companies are less prone to file patents than large companies. Since smaller companies may tend to be younger too, they indicate that innovation in startups may not be accurately measured using patents.[24] This may provide some insight into this research paper in terms of understanding the demographics of the most patent innovative Swedish companies and to what extent profitability and age interact with patent levels. Although the authors do not specifically discuss the case of Swedish patenting, smaller and likely younger companies in Sweden may be less inclined to file for patents too. This could mean that company age plays a role in determining what firms register patents in a Swedish context, or that other factors potentially correlated with age such as size or profits matter.

Additional insights can be found from OECD’s “SME and Entrepreneurship Outlook 2019” report. According to this report, smaller companies engage in less research and development, leaving them to rely less on internally curated knowledge. Similar to what Klenow and Li noted for the U.S., aggregate research into patentable innovation tends to be concentrated to a smaller share of all firms among OECD-countries, and be more common among larger companies. With the reasoning of Klenow and Li, this may mean that older, profitable companies that potentially tend to be large could constitute leaders within patenting OECD-wide. Another point relating specifically to patenting brought up in the OECD-report states that “Progress in SME patenting may remain limited for lack of awareness, interest and a limited SME participation in business

[18] Blind K., Cremers K., Mueller E., The Influence of Strategic Patenting on Companies’ Patent Portfolios, Centre for European Economic Research, page: 1/“Non-technical Summary”, 09/2008

[19] Pakes A., Griliches Z., Patents and RD at the firm level: A first report, ECOLET, pages: 289-295, 1980

[20] Henkel J., Reitzig M., Patent Sharks, Harvard Business Review (HBR), 06/2008

[21] Farre-Mensa J., Hegde D., Ljugqvist A., The Bright Side of Patents, National Bureau of Economic Research, 2016

[22] Kiraci M., Celikay F., Celikay D., The Effects of Firms’ RD Expenditures on Profitability: An Analysis with Panel Error Correction Model for Turkey, International Journal of Business and Social Science, pages: 233-234, 05/2016

[23] Swedish Institute, Innovation in Sweden, 03/05/2021

[24] Klenow P., Li H., Innovative growth accounting, Vox, 18/08/2020

RD".[25] That as it may be, research and development could also be a combination of different processes that are not easily measured or captured in a classical sense.[26] With Swedish spending on research and development relative to GDP being markedly higher than the Europe and world average[27], Swedish companies may rely on different resources for spending on research. If capital markets are different in Sweden compared to other OECD countries, profits and age may not matter as much if young, small firms have easier access to cash that can be utilized for research purposes.

According to existing research on this topic, the Swedish investment markets do seem to stand out. In a European context, Sweden has had one of the highest levels of capital invested, standing out as a country with particularly many deals and billion dollar valuation companies created. Overall, the Swedish capital markets appear particularly attractive and accessible with one of the highest levels of accumulated investments in Europe since 2013.[28] This could mean that the connection between patenting and firm characteristics likely correlated with company size such as profits and age may be less clear in Sweden if younger firms have easier access to external capital. Moreover, the demographics of how different companies choose to finance the costs of research and development may also vary to some extent. In the research paper "The Financing of Research and Development", author Bronwyn H. Hall concludes that large firms tend to use internal funding in financing research, noting also that there may be limitations to externally raised capital for new firms.[29] This highlights the complexity of research financing, and indicates a demand for more research into the role that profits play, perhaps especially for younger firms that are not necessarily very large in Sweden.

4 Research Focus

4.1 Specification of Research Focus

There seems to be a tendency for large, likely profitable and experienced companies to dominate within the field of patenting internationally, and existing literature indicates that financial resources do affect patenting levels. This leads to the suggestion that younger, less profitable Swedish companies may be less engaged and effective within patenting. But, the Swedish case may require further consideration. The fact that Swedish capital markets stand out from an international perspective opens up for several potential expeditions of research into what factors matter for Swedish firms. If outside capital does act as a vast source of funding, the financial markets in Sweden may change what forces help drive patentable innovation among top innovators. A case could be made that young Swedish companies may have greater access to external capital than in some other OECD-countries that can be deployed on research and development: possibly helping them generate more patents without them necessarily having to be large, profitable or old. Is profitability actually needed for the patent creation process, and what effect does it have? Simultaneously, does age matter in a Swedish context in understanding what companies register more patents than others, and to what extent may it be a relevant predictor of patent innovation in firms?

The extent to which profits and firm age are relevant factors for patent generation among dominating companies in Sweden, and in what potential ways, becomes a particularly interesting topic of further research. The current existing literature in combination with available firm-level financial and patenting data should be sufficient to research the following research question.

4.2 Research Question

Do firm age and year-to-year profit-levels matter predictively for the number of Swedish patents registered per year during the period 2010-2013 among top patent innovators in Sweden?

[25] OECD SME and Entrepreneurship Outlook 2019, Access to innovation assets, Organisation for Economic Co-Operation and Development (OECD), chapter 7, 20/05/2019

[26] Zettelmeyer F., Hauser J.R., Metrics to Evaluate RD Groups Phase I: Qualitative Interviews, Massachusetts Institute of Technology, 07/03/1995

[27] Swedish Institute, Innovation in Sweden, 03/05/2021

[28] The State of European Tech, Another record breaking year for European tech, Atomico, pages: 107-111, 04/12/2018

[29] Bronwyn H., The Financing of Research and Development, Oxford Review of Economic Policy, 2002

5 Method

5.1 Econometric Model and Quantitative Design

On a fundamental level, a model sufficiently advanced to answer the research question to a satisfactory degree requires consideration of not only what data is available on the topic, but also of how this data is ordered and what control variables need to be included. The econometric model will rely on short time series data from 2010-2013, and the main analysis will utilize fixed effects to capture the interactions between firm profits, age and number of patents registered within a company. Since fixed effects may cancel out some variables due to perfect multicollinearity, which is when there is a perfect linear relationship between explanatory variables[30], a more general short time series random effects model including these variables too will also be used. This will provide a contrast to the main fixed effects framework.

This model design is chosen for several reasons, and relies on a number of assumptions. The fact that the financial crisis of 2008 may have had potential effects on the economy in ways that may have interacted with the propensity to file patents in the years following was something we also considered. Should the financial crisis have affected profits and intended spending on for example research and development or number of employees, this would need to be considered in the model design. Additionally, there may potentially have been disproportionate and perhaps asymmetric effects on young start-up companies and older, historically profitable companies. As a result, using time-series data to some extent could prove valuable. This would also allow us to capture and control for any potential time-trend effects stemming from the crisis, whilst still keeping the analysis relevant from a time-perspective. Moreover, restricting the data to the year 2013 ensures that the data is complete, with the assumption being that there may be patents pending still for later years. There appears to be support for this by looking at available data in the PAtLink database, covered more extensively in section 6.3.1. Furthermore, utilizing fixed effects in the regression allows us to fix company effects systematically for our analysis. Fixed effects as a concept is described in detail in section 5.3.3. The main argument for this is that it allows us to capture effects that stem from differences between rather than within companies, which helps answer the research question of what separates the most innovative companies from the rest.

The selection and analysis of what control variables are to be included also relies on various assumptions, and requires consideration of the current literature on the topic. Within the context of understanding the effects of profitability and company age, variation closely related to these variables should naturally be in focus as potential control factors to account for potential omitted variable bias. Omitted variable bias, which can occur if a variable that correlates with another explanatory variable as well as the dependent variable is left out, could lead to misrepresentation of true coefficient values.[31] This being true however does not necessarily mean that controlling for all the various variables that directly or indirectly covariate with the number of patents registered is neither possible nor desirable. The ultimate goal of the model within this research paper is not to explain all variation in the number of patents registered on a company level. As a result of this, data on variation within revenues, number of employees, and efforts within research and development was made relevant. Furthermore, the fact that patents can be registered for different forms of inventions, that may vary in their profitability and that may be more or less common within different sectors, provides grounds for assuming that industry-controls could be valuable. Including industry variables may also provide value if general access to capital markets or profitability differs across sectors.

Avoiding covariation from the fact that more profitable companies may tend to spend more resources within the area of research and development poses several challenges. In part, it could be important to consider how profit-levels and spending on research and development may be connected. To the extent that profits may help finance research that may have an effect on patenting-levels, any controls for research and development may also in part be related to profits. Moreover, there may be challenges in choosing how to measure research efforts. Some variation in accounting preferences and methods may be controlled for through including sectors in the econometric model, but differences in how companies choose to account for

[30]Metropolitan State University, Multicollinearity

[31]Buck S., University of California, Berkeley, Discussion of Omitted Variable Bias versus Multicollinearity, 2015

research expenses may still be idiosyncratic to a large degree. To avoid discrepancies from the fact that companies may register research and development expenses in varying ways even within sectors, controlling for intangible assets appeared a valuable alternative.

Intangible assets include not only the value of patents and similar rights, but also capitalized expenditure for research and development, goodwill and more.[32] Using intangible assets as an index for research will likely include noise in the measurement in regards to capturing research and development expenses, but may still diminish overall omitted variable bias efficiently. Moreover, considering the fact that one of the fundamental purposes of patenting as a legal tool to begin with is to encourage long-term spending on research[33], including intangible assets over time may also be relevant. If current profits are highly correlated with the level of spending on research many years prior to the period 2010-2013, this becomes necessary to control for. We will do this by also including an average intangible assets variable containing firm-level data from the years 2005-2009. By also including the number of employees as a variable, omitted variable bias from covariation between company size, profits and age is likely diminished too. This may also indirectly help control for spending on research and development, which is likely correlated with company size.

To summarize, we will mainly use a short time series regression considering fixed effects in order to examine how profitability and company age affect the number of registered patents a company produces per year. For the fixed-effects regression, control variables for revenue, number of employees and intangible assets will be included, as well as year-dummies. For the more general random effects regression, variables that do not vary on a company level across years will be included also. By controlling for several variables such as revenues which may be highly correlated with profits, age and patent-levels, less biased coefficients may be obtained. Furthermore, potentially significant control factors may also help shine light on the effects of profits and age too. The fixed effects model as well as the wider model including all variables that will be used will take the following form

$$\begin{aligned} Pat_{it} = \beta_0 + \beta_1 Prof_{it} + \beta_2 Rev_{it} + \beta_4 NumEmp_{it} + \beta_5 IntA_{it} + \beta_6 2010_t + \beta_7 2011_t + \beta_8 2012_t \\ + \beta_9 2013_t + u_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} Pat_{it} = \beta_0 + \beta_1 Prof_{it} + \beta_2 Rev_{it} + \beta_3 RegYr_{it} + \beta_4 NumEmp_{it} + \beta_5 IntA_{it} + \beta_6 AvgIntA_{it} \\ + \beta_7 EngyEnv_{it} + \beta_8 Mat_{it} + \beta_9 IndstG_{it} + \beta_{10} ShopG_{it} + \beta_{11} HthEd_{it} + \beta_{12}\mathrm{ITElec}_{it} \\ + \beta_{13} CorpServ_{it} + u_{it} \end{aligned} \tag{2}$$

Extended information about the variable names in the equations can be found in section 11.1, Econometric Model Variables and Description

5.2 General Econometric Concepts

In order to perform the analysis that we intend, we require several mathematical models and assumptions obtained from econometrics. Hence, this section is meant to provide background on the mathematical models and assumptions used to perform our analysis. In addition, we also explain why the mathematical models and assumptions are relevant to our models.

5.2.1 Multiple Linear Regression Analysis

This simple multiple linear regression (MLR) is, in fact, not used in our study but is yet included in this section as it lays the foundation for all the other models that were used. Understanding the MLR model makes it also easier to comprehend the upcoming models. The MLR is defined as an econometric tool used to estimate the relationship between two or more independent variables and a dependent variable by fitting a linear equation to observed data. The goal of MLR is thus to model the linear relationship between the independent variables and the dependent variable. The linear equation employed for fitting the empirical

[32] Weidenman P., The Serrano Database for analysis and register-based statistics, Bisnode, page: 74, 01/2016
[33] Hellstadius Å., Immaterialrätt och marknadsrätt - ur praktiskt perspektiv, page: 43, 14/08/2020

data is given by

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + u \tag{3}$$

where y corresponds to the dependent variable and x_i corresponds to the independent variable. The coefficient, β_i, is the parameter obtained from fitting the data and is associated with x_i. The coefficient, β_i, can be interpreted as the effect on y from a one-unit change in x_i, holding all other independent variables fixed. Lastly, u constitutes the error term and is the difference between the estimated value given by the model and the actual value observed. Due to how the MLR model is constructed, the error term is minimized and has the expected value of zero. [34]

5.2.2 Gauss-Markov Assumptions

The MLR is based on five assumptions named the Gauss-Markov assumptions that are used in order to obtain an unbiased estimator. Having an unbiased estimator is essential since a biased estimator would mean that the estimator's expected value does not correspond to the actual value of the estimated correlation, thus giving an incorrect model. To obtain an unbiased estimator, it is sufficient that only the first four Gauss-Markov assumptions are fulfilled. The fifth assumption is required when wanting an unbiased variance.[35] However, it is crucial to check how well the data matches these assumptions. If a condition is violated, it is possible to use different econometric methods or change the setup to improve the fulfillment of the Gauss-Markov assumptions.[36] In practice, the Gauss-Markov assumptions are rarely met perfectly, but they are still helpful as a benchmark and show us what the ideal conditions would be. The Gauss-Markov assumptions are given by:

- **MLR.1 - Linear in parameters**
  The linear regression requires a linear relationship between the dependent and explanatory variables. [37]

- **MLR.2 - Random sampling**
  The second assumption asserts randomization of the sample data, implying that the values for an independent variable should not be correlated. However, this assumption is omitted when a time series regression is utilised as then you purposely organise the data by year. [38]

- **MLR.3 - No perfect collinearity**
  No explanatory variables should be constant, and there should not be any exact linear relationship between explanatory variables.[39] However, it should be pointed out that "no perfect collinearity" does not mean that two independent variables cannot be correlated. Rather it only encompasses perfect linear correlation. [40]

- **MLR.4 - Zero Conditional Mean**
  The expected value of the error term should be zero regardless of what values the independent variables obtain.[41] In other words, this implies that there are no omitted variables that have been excluded that correlates with one of the independent variables. If this is not the case, this would mean that a necessary factor has been left out. Something that will lead to incorrect conclusions on inference by over- or underestimating our included variables' effect.[42] Mathematically this is expressed as:

$$E(u|x_1, x_2, ..., x_n) = 0 \tag{4}$$

[34] Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 3.
[35] Ibid, Chapter 3
[36] Östling R., 2020, Multiple Linear Regression: Further Issues - Lecture 8, [Powerpoint presentation]
[37] Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 3.
[38] Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 10.
[39] Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 3.
[40] Studenmund A. H. , Using Econometrics: A Practical Guide, sixth edition, (Pearsons, 2014), 98.
[41] Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 3.
[42] Östling R., Simple Linear Regression II - Lecture 3, [Powerpoint presentation], 2020

- **MLR.5 - Homoscedasticity**
  The fifth assumption asserts a constant variance across the error term. In other words, the error term u should have the same variance given any value of the independent variables, which mathematically is expressed as [43]
  $$Var(u|x_1, x_2, ..., x_n) = \sigma^2 \tag{5}$$
  This assumption is usually regarded as less significant than the previous ones as it has no bearing on the unbiasedness of the estimator, $\hat{\beta}_i$. However, homoskedasticity has two crucial implications. Firstly, we can derive formulas for the sampling variances whose components are easy to characterize. Secondly, we can conclude that under the Gauss-Markov assumptions the OLS estimators have the smallest variance among all linear, unbiased estimators.[44] If the data is not homoskedastic, it is heteroskedastic. Heteroskedasticity is a common problem in regression analysis as it invalidates statistical tests of significance that assume that the error term's variance is constant. However, this can be controlled for using robust standard errors, which we describe in more detail in section 5.3.4. below.

5.2.3 Dummy Variables

A well-known econometrics tool that we use when controlling for industries in our model is dummy variables. A dummy variable is a numeric variable that takes the values 0 or 1 to indicate the absence or presence of some categorical data. In other words, it enables controlling for qualitative data that may be expected to shift the outcome.[45] Hence, when controlling for industries, dummy variables made it possible to observe the impact of belonging to a specific industry or not.

5.3 Model-Specific Concepts

5.3.1 Time Series

So far, we have been concerned with the MLR model that has random samples of cross-sectional data, which does not consider the data's time dimension. However, in many cases, you can have data from different time periods, and suddenly the time dimension is of interest. When working with data that varies in time, the time dimension itself can impact the result, which must be accounted for as it otherwise would result in a biased outcome. This type of data is named time series data and results in regression assumptions and models that differ from the previous MLR model.[46] In our case, the time dimension was relevant, which made us use models that considered the time dimension.

5.3.2 Panel Data

In econometrics, panel data is a dataset that has both a cross-sectional and a time-series dimension.[47] Meaning that observations are made for a subject each time but in different periods. A good example would be the dataset below:

Company	Year	Number of employees	Profit
A	2001	43	$ 53 000
A	2002	44	$ 46 000
B	2001	25	$ 12 000
B	2002	26	$ 9 000

Here we have a dataset with a panel structure where individual characteristics are collected for different subjects and years; company A and B are observed every year for two years (2001, 2002).

[43] Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 3.
[44] Östling R., Multiple Linear Regression: Estimation - Lecture 4, [Powerpoint presentation], 2020
[45] Östling R., Simple Linear Regression II - Lecture 3, [Powerpoint-presentation], 2020
[46] Östling R., Basic Regression Analysis with Time Series Data - Lecture 10, [Powerpoint presentation], 2020
[47] Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 13.

5.3.3 Fixed Effect Regression

The Fixed effects (FE) regression model is perhaps the most significant model in our research as we used this model mainly. The purpose of the FE model is to control for omitted variable bias due to unobserved differences across clusters that are constant over time. The regression can thus be applied to panel data sets to control time-invariant unobserved characteristics correlated with the observed explanatory variables.[48] In other words, the main advantage of this transformation is that we do not have to worry that the unobserved fixed effect causes omitted variable bias.

An assumption made to derive the formula for the FE regression is that the error term can be separated into an idiosyncratic, u_{it}, and fixed part, a_i, that together constitute the total error, v_{it}=u_{it}+a_i. The distinction between the parts is that the idiosyncratic part changes over time, and the fixed part is time-invariant. The derivation of the formula then results in that the fixed part vanishes, and only the idiosyncratic error term is left. That is why fixed effects do not cause any omitted variable bias problem when using this regression. The equation for the FE regression is shown below.[49]

$$\ddot{y}_{it} = y_{it} - \bar{y}_i, \qquad \bar{y}_{it} = \frac{1}{T}\sum_{i=t}^{T} y_{it}$$

$$\ddot{x}_{it} = x_{it} - \bar{x}_i, \qquad \bar{x}_{it} = \frac{1}{T}\sum_{i=t}^{T} x_{it}$$

$$\ddot{u}_{it} = u_{it} - \bar{y}_i, \qquad \bar{u}_{it} = \frac{1}{T}\sum_{i=t}^{T} u_{it}$$

$$\ddot{y}_{it} = \beta_1\ddot{x}_{1,it} + \beta_2\ddot{x}_{2,it} + ... + \beta_k\ddot{x}_{k,it} + \ddot{u}_{it} \tag{6}$$

The fixed effect regression requires, precisely as in the MLR model, that several assumptions are met before it can be used. The assumptions are very similar to the Gauss-Markov assumptions but with minor modifications that regard the time-series dimension in the data. These assumptions appear reasonable within our model, however cluster robust standard errors (see section 5.3.4) were used to control for potential heteroskedasticity. The assumptions are listed below.[50]

- **Assumption FE. 1-3** Besides the time aspect, the first three assumptions are practically indistinguishable from the first three Gauss-Markov assumptions. The first assumption, FE. 1, assumes that there exists a linear relationship between the dependent and independent variables. Compared to MLR. 1, the only difference is that this has to hold for all time periods. The second assumption, FE. 2, states that the sample has to be randomised but only within the cross-section. Finally, the third assumption, FE. 3, states that no explanatory variable should be constant over time or have perfect linear relationships with each other. [51]

[48] Östling R., Panel Data Methods I - Lecture 12, [Powerpoint presentation], 2020
[49] Ibid, Lecture 12
[50] Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 13.
[51] Ibid, Chapter 13

- **Assumption FE. 4**
This assumption is similar to the fourth Gauss-Markov assumption regarding the zero conditional mean (MLR.4). However, the FE model requires a stronger assumption called strict exogeneity. Strict exogeneity implies that the error term not only needs to be zero regardless of the independent variables' values, this need also to hold for every time period.[52] However, in the FE model, only the idiosyncratic error term is relevant. Therefore, another condition is added. The expected value of the idiosyncratic error term has to be zero regardless of the fixed error term's value. These conditions can all be summarized by the formula [53]
$$E(u_{it}|x_1, x_2, ..., x_n, a_i) = 0 \tag{7}$$
If this assumption FE. 4 combined with the previous assumptions, FE. 1-3 are satisfied, then the fixed effects estimators are unbiased.[54]

- **Assumption FE. 5**
The fifth assumption states that the idiosyncratic error term should have the same variance regardless of the independent variables' values and the fixed error term's value. The assumption can be summarized by the equation[55], however within our analysis cluster-robust standard errors will be used (discussed further in the following section).
$$Var(u_{it}|x_1, x_2, ..., x_n, a_i) = Var(u_{it}) = \sigma^2 \tag{8}$$

- **Assumption FE. 6**
Unlike the previous assumption, the sixth assumption does not have an analogous assumption with the Gauss-Markov assumptions as this assumption becomes more relevant when working with time-series regressions. The assumption states that there should be no serial correlation among the idiosyncratic error terms. Meaning that the idiosyncratic error terms should be uncorrelated with each other in different time periods. If this is not taken to account, the precision of the estimated coefficients will be overestimated, i.e., the variance of the estimators will be underestimated. The equation that describes this assumption is given by[56]
$$Cov(u_{it}, u_{is}|x_1, x_2, ..., x_n, a_i) = 0, \quad t \neq s \tag{9}$$
Serial correlation is relatively normal, so one common method to avoid serial correlation is to use cluster-robust standard errors.[57]

5.3.4 Cluster Robust Standard Errors

Robust standard errors is an econometric method used to avoid biased variances of the estimators under heteroskedasticity or serial correlation.[58] Within the regressions that will be based on the empirical models outlined above, robust standard errors across clusters will be used. This will be carried out through the vce(robust clustvar) STATA-command.[59] This will not have an effect on the regression coefficients, but should serve to decrease bias within the models.[60] Using cluster robust standard errors appears supported further since the dataset may be viewed as to contain a small share of clusters from the larger population of companies that have registered patents between 2010-2013.[61]

[52] Östling R., Panel Data Methods I - Lecture 12, [Powerpoint presentation], 2020
[53] Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 13.
[54] Östling R., Panel Data Methods I - Lecture 12, [Powerpoint presentation], 2020
[55] Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 13.
[56] Ibid, Chapter 13
[57] Östling R., Panel Data Methods I - Lecture 12, [Powerpoint presentation], 2020
[58] Ibid, Lecture 12
[59] StataCorp, xtvce_options, Stata Manuals, 2021
[60] Williams, R. University of Notre Dame, Heteroskedasticity, 10/01/2020
[61] Heim A., Paris School of Economics, When should we adjust standard errors for clustering?, 02/10/2019

5.3.5 Random Effects Regression

The Random effects (RE) model was, like the FE model, also used for several tests in the research. The RE model was mainly included to provide a comparison to the FE model as they are identical except for one assumption. The assumption is that in the RE model, it is assumed that the fixed error term is uncorrelated with the explanatory variable.[62] In contrast to the FE model, where they are assumed to be correlated. Except for the assumption about the no correlation between the fixed error term and the independent variable, the models are identical, and both are based on the same assumption, FE. 1-6.[63]

5.3.6 Finite Distributed Lag

The finite distributed lag model is used as part of our analysis. This model uses a regression equation that predicts the current values of a dependent variable based on both the contemporary values of an independent variable and previous ones from the past periods (lag weights).[64] How many lag weights you want to use is unrestricted. However, it is a trade-off with the number of degrees of freedom. With that in mind, we decided only to use one lag weight in our regression. The use of this model is that it controls for effects that may emerge due to the time dimension. The assumptions needed for this are very similar to the assumptions mentioned in the fixed effects model.[65]

6 Dataset and Sources

6.1 Developing the Dataset

To enable research into whether or not profitability and firm age can help explain the mechanics of what constitutes the most technically innovative Swedish companies, we have leveraged the extensive amounts of detailed firm-level data from the Serrano and PAtLink Databases. To be able to answer the research question aimed at the most technically innovative Swedish companies, the decision was made to only include companies that had registered five or more presently approved patents over this four year period.

Recognizing that patents are added to the PAtLink Database on an ongoing basis, the data for the years 2014-2018 was initially excluded to minimize the risk of analyzing years with a high share of still pending applications. The process of developing the dataset to be used in the quantitative analysis then advanced to merging the different patent-datasets. Continuing on this, data on all other years than 2010-2013 were removed, and duplicates across files were excluded through filtering on the unique appln_nr_epodoc and appln_id variables. After this, the dataset was filtered on the appln_auth variable through the "SE" value to limit the data to patents filed in Sweden. Individuals included as patent owners were also filtered out. From this data, we randomly selected 40 individual firms with the defined constraint of having registered at least five patents over the chosen time period. At this stage, a list of 40 firms with at least five patents registered over the four years 2010-2013, along with information about what number of patents were filed annually over that period, had been gathered. To complete the dataset, we gathered model relevant data from the Serrano Database for the variables specified in the econometric models, see section 5.1. Variable names and short selection commentary can be found in the Appendix section 11.1. This process was carried out through filtering the Serrano STATA-files on organizational number. No data was left out of the dataset, and when corrupt or lacking data points were encountered, these were marked as blank entries in our dataset.

6.2 About the Dataset

This section intends to give an overview of the dataset and present some key characteristics of the companies included. The dataset consists of 40 companies that compose a balanced mixture of old and young firms with the majority being spread out across the 1900s, with most companies being around 30 years old. Younger companies in the dataset tend to have fewer employees and lower profit-levels, which is expected from the

[62]Östling R., Panel Data Methods II and Instrumental Variables - Lecture 13, [Powerpoint presentation], 2020
[63]Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 13-14.
[64]Östling R., Basic Regression Analysis with Time Series Data - Lecture 10, [Powerpoint presentation], 2020
[65]Wooldridge M. J, Introductory Econometrics: A Modern Approach (Cengage Learning, 2012), Chapter 10-12.

current literature. Most companies have employee numbers in the hundreds. All companies have at least five registered patents in total for the four years 2010-2013, and the number of patents appears to move together and correlate with other variables such as profits and revenue. The companies' profits have a wide variation in the dataset, with the majority of companies across all years showcasing profitability. The average profit-level is around 600 million SEK, and perhaps expected, the profits variable correlates strongly with the revenues variable, with a correlation of circa 0.9. On average, the intangible assets variable for 2010 through 2013 is larger than the average intangible assets variable for the period 2005 through 2009, which may possibly relate to the market conditions around the financial crisis of 2008. The companies in the dataset are also active within several different business sectors, ranging from the energy sector to the shopping goods sector. Industrial goods is the most common business across all companies.

6.3 Dataset Sources

6.3.1 PAtLink Database

The PAtLink database, provided by the Swedish House of Finance, contains both patent and trademark information on a firm-level for Swedish companies. The goal of the PAtLink project "is to create and free of charge distribute a comprehensive matching file between patent and trademark information and organizational information". The patent-datasets contain information on all patents pertaining to Swedish firms, and in part include information on individuals too, in total stretching between the years 1990 and 2018. While the degree to which company-level information is available between the different patent datasets varies, categorizable features such as filing year and unique identifier codes are included across all data for all years. Patents are added to the dataset on an ongoing annual basis, resulting in fewer registered patents listed for the years leading up to the presently final available year 2018.[66] Patent data is collected from the PATSTAT database[67], which in turn is provided by the European Patent Office, EPO[68]. Meanwhile, the PAtLink database is provided free of charge by the Swedish House of Finance and is financed by Vinnova[69], the Swedish government innovation agency.[70] The Swedish House of Finance is connected to the Stockholm School of Economics, and was founded by SSE and the Institute for Financial Research.[71] The use of this data is contingent on some terms, which is covered more extensively in section 10.4.

6.3.2 Serrano Database

The Serrano Database is provided by the Swedish House of Finance, and contains firm level financial and general information for Swedish companies. The datasets are constructed using financial statements submitted to the Swedish Companies Registration Office, Bolagsverket, information from Statistics Sweden, SCB, and the private company Bisnode.[72] Bisnode is a global data and analytics company that works with helping firms and government agencies form data-driven solutions.[73] The different datasets contained within the Serrano Database framework cover most areas of business, both internal as well as external operations. Moreover, the database is "controlled and quality assured", and is updated semi-annually. Data was gathered from the November 2020 version. A prominent feature of the datasets provided is that the data is altered in several ways, to account for factors such as differing lengths of accounting periods between firms and what constitutes a start-up.[74] There are some restrictions and stipulations for how this data can be used and in what contexts, which is covered in the following section 10.4.

[66] Swedish House of Finance, About the PAtLink dataset, 202
[67] Ibid, 2021
[68] European Environment Agency, EPO Worldwide Patent Statistical Database (PATSTAT), 09/03/2020
[69] Swedish House of Finance, About the PAtLink dataset, 2021
[70] Vinnova, About us, 2021-02-19
[71] Anders Anderson, Swedish House of Finance, Background, 2021
[72] Swedish House of Finance, About Serrano, 2021
[73] Bisnode - A Dun Bradstreet Company, Bisnode - A Dun Bradstreet Company
[74] Swedish House of Finance, About Serrano, 2021

7 Analysis

7.1 Empirics

7.1.1 Expectations on Coefficient Values

Several estimations could be made about the expected relationships between company profits, age and number of patents registered per year - as well as between the other control variables. Considering the current literature on the topic, we would expect intangible asset levels to have a positive sign within our fixed effects regression. Otherwise, companies would likely not spend resources on research and development, or patenting would perhaps not serve a purpose. The fact that larger companies tend to turn to patenting more frequently in general, as brought up in the article by Klenow and Li, further leads us to expect the number of employees to be positively correlated with the number of patents registered per year. Moreover, by looking at the dataset, we would expect the revenues variable to have a positive sign too, which also appears supported by existing literature on what companies tend to patent the most. The sign of the profits variable however is more difficult to predict.

One expectation from the existing literature could be that profits would be associated with a positive sign. More profitable companies likely have more cash to spend on research or other forms of less tangible supporting activities that generate patents, and they are likely also larger too. However, the extent to which that effect gets cancelled out when controlling for other variables such as revenues, intangible assets or size is more difficult to predict. All in all, we would expect profits to be positively correlated with the number of patents registered on a company level.

For the more general random effects regression without fixed effects, coefficients for various industry dummy variables, company age and average intangible assets are calculated. As regards the industry variables, it seems plausible to expect that sectors where patents are relatively more financially important may have positive signs. It seems likely that more technically oriented industries may engage more in patenting, which is technically oriented, and may have positive signs. However, the extent to which differences in industry actually matter within the context of analyzing 40 of the most patent active Swedish companies is difficult to estimate. As regards the average intangible assets variable, with information on the average level of intangible assets between 2005-2009, we would expect it to have a positive sign in line with current literature. This may however not be the case, should the averaging of the years remove too much variation. In that case, the sign may instead be negative. Finally, we would assume the age variable to have a negative sign, meaning that older companies would be expected to be associated with more patents registered annually. This is aligned with current literature in the sense that older companies likely are larger companies, which tend to pursue patenting. However, as other factors such as revenues and spending on research and development is included, this reasoning becomes less straightforward. It may be the case that a young company that has received heavy investments or that has very high profit-levels may be as patent innovative as similar older companies.

7.1.2 Empirical Tests and Results

The short time series fixed effects regression presented the following results:

Number of Observations	148
Number of Groups	39
R^2	
Within	0.4545
Between	0.2635
Overall	0.1554

Independent Variables	Coefficient	Robust Standard Errors	t	$P >\mid t \mid$	95% Confidence Interval	
Profit (per Billion SEK)	1.06	0.375	2.83	0.007	0.303	1.82
Revenue (per Billion SEK)	3.79	1.03	3.67	0.001	1.70	5.88
Number of Employees	-0.0218	0.0087	-2.49	0.017	-0.0395	-0.0041
Intangible Assets (per Billion SEK)	5.89	1.05	5.59	0.000	3.76	8.98
Year						
2011	0.8094	0.4306	1.88	0.068	-0.0624	1.6811
2012	1.3279	0.6805	1.95	0.058	-0.0497	2.7054
2013	1.0401	1.0541	0.99	0.330	-1.0938	3.1740
Constant	0.0562	2.0029	0.03	0.978	-3.9985	4.1108
σ_u	16.9978					
σ_e	2.90423					
ρ	0.9716	(Fraction of variance due to u_i)				

Table 1: Fixed Effects

From this regression, several results can be noted. The number of observations included in the regression is listed as 148, which is slightly lower than the 160 observations that might have been expected with four time-periods across 40 companies. This can be explained by the fact that not all companies had data for all years, which is expected. Moreover, all variables have positive signs except for the variable for the number of employees, indicating that there is a positive relationship between profits, revenue, intangible assets and the number of patents each company produces per year on average. For every one billion Swedish SEK made in profits, 1.06 additional patents registered per year is expected. That holds true also for revenues and intangible assets, with an additional billion SEK being associated with 3.79 and 5.89 additional patents registered per year on average respectively.

Furthermore, all variables except the time-trend variables are statistically significant at a 95% significance level. This indicates that the correlation coefficients for the main variables estimated through the regression are of substance, and that they are not necessarily affected by any year-to-year trends. Meanwhile, the company age variable is statistically insignificant with a P-value of 0.819 in the random fixed effects regression (see Appendix section 11.2). That is also the case with all different sector variables, which appear systematically insignificant even at a 90% significance level (see also Appendix section 11.2). The contrary is true for the average intangible assets variable containing averaged data for the years 2005-2009, which is statistically relevant at a 95% significance level with a P-value of $0.028 < 0.05$ and a negative coefficient (Appendix 11.2). For every increase in average intangible assets over the preceding five year period of one billion SEK, an associated decrease of 12.2 patents per year is expected. This is against what was expected, and the averaged variable appears to follow a different pattern than the intangible assets variable in the fixed effects regression. That variable had a positive sign but a less substantial associated correlation. This indicates that the variation in year-to-year differences in levels of intangible assets relies on other underlying mechanics than the variation in averages over several years.

7.2 Discussion and Interpretation of Results

7.2.1 Understanding the Control Factors

These results provide information not only on the underlying relationship between firm-level profits, age and number of patents registered per year, but also on the effect of other related variables that profits and company age may interact with. On a fundamental level, it is essential to acknowledge that any statistically significant coefficients associated with any variables mark correlation. While correlation is required for there to be grounds for causality, correlating variables need not be immediately connected. Regardless, the overarching results from the quantitative analysis are in line with expectations from existing literature and theory.

Fundamental economic theory on the topic of production, viewing it as a combination of labor, capital and some total factor productivity on an aggregate level, appears to be aligned with our results even on a micro-level. Firms with higher revenues and higher profits tend to register more patents per year for this period. At the same time, the relationship is not fully clear at first glance. While the coefficients for profits and revenues had positive signs, the number of employees variable had a negative sign, indicating that the marginal effect on the number of patents registered was negative for additional employees. The fact that labor is part of the production process, as one input factor, is expected from economic theory. For every additional 100 employees, there would be an associated decrease in the number of patents registered by roughly two. This likely stems from the fact that an increase of 100 employees for most of the companies in the dataset would be a substantial increase. This could be interpreted as signifying that labor has a negative effect as an input variable, and that productivity and capital levels matter more, at least within the dataset. However, the negative coefficient for the number of employees cannot always be negative - someone must participate in the innovation creation process that leads to patents. A likely reason for the negative coefficient for the number of employees variable might be that the most patent innovative Swedish companies included in the dataset already had sufficiently many employees on average in relation to other resources deployed within patent production. Holding profits, revenues and intangible asset levels constant, additional employees may not provide sufficient value to the patent creation process. Rather, they may reduce other resources linked to capital- or productivity-levels not clearly accounted for within the framework of the model that have a causal link to the number of registered patents. This being true, the implications of fundamental macroeconomic theory appears to be in line with what the model predicts.

Furthermore, U.S. data predicted there to be some form of general link between research and development and patenting levels. This is also something that can be expected from a legal standpoint as a fundamental reasoning behind why patents exist to begin with, to protect revenues and profits from original solutions against the losses in the production of those same innovations. The fact that the intangible assets variable has a positive correlation coefficient is thus aligned with other empirical results and theory. Meanwhile, the fact that the variable for average intangible assets has a negative correlation coefficient (see Appendix section 11.2) is less straightforward. The two variables relate to the same phenomena, levels of intangible assets, however they vary in different ways and in part represent different things.

While the intangible assets variable varies year-to-year, and thus can be included in the fixed effects regression, the average intangible assets variable is constant on a company level and does not vary year-to-year during the period 2010-2013. This potentially matters because of what the average could represent. The core components of the intangible assets variable include the value of patents and similar rights, goodwill, capitalized expenditure on research and development and more. It is likely that capitalized expenditure on research and development is captured in the year-to-year variation that the intangible assets variable measures. However, for the average intangible assets variable, the variation used in the model is the differences in total levels between companies over several years - and large parts of the variation in this may mainly come from differences in goodwill or other types of intangible assets. While variation in the bulk of the intangible assets value is significantly negatively correlated with the number of patents registered, year to year changes likely stemming from variation in capitalized research expenditures are significantly positively correlated. This could explain the differences in signs between the two variables. The average intangible assets variable may still be useful in reducing omitted variable bias for the profit and company age variables, even though the interpretation of its coefficient is not straightforward. For the purposes of the role that research is expected to play in the patent creating process, the results are expected according to previous studies and literature on the topic.

The purpose of including control variables for factors such as intangible assets, revenues and number of employees was to reduce omitted variable bias in relation to the relationships between firm profits, age and patenting levels. The main control variables included appear to follow our expectations from current literature and theory. This provides some guidance in the sense that our model seems to produce replicable and sensible results. Analyzing if profitability and firm age can help explain what separates the most technically innovative Swedish companies from the rest may thus be facilitated by including these control factors on a conceptual level.

7.2.2 Implications of Empirical Results on Research Question

The implication from existing literature was that larger firms had a higher propensity to patent than smaller firms. With larger firms likely being older and smaller firms likely younger, the conception was that firm age could be a relevant indicator of patent-levels. The extent to which profits would matter for firm patent levels however was less clear for the Swedish case. Smaller and likely younger firms engage in less research within the OECD-region. However, relatively more is spent on research and development in Sweden than most other countries in the world, and capital markets are relatively active which could benefit young firms. What role would profits and age serve within the dynamics of patent creation? This was the point of entry for the analysis, and it was not clear how the variables would interact with patenting among the most patent innovative Swedish companies. An excerpt for the results on the relationship between firm profits, age and the number of patents registered per year is presented below in Table 2 and 3:

Independent Variables	Coefficient	Robust Standard Errors	t	$P >\mid t \mid$	95% Confidence Interval	
Profits (per Billion SEK)	1.06	0.375	2.83	0.007	0.303	1.82

Table 2: Fixed Effects Regression Correlation Coefficient

Independent Variables	Coefficient	Robust Standard Errors	t	$P >\mid t \mid$	95% Confidence Interval	
Profits (per Billion SEK)	0.663	0.133	5.00	0.000	0.404	0.923
Registration Year	-0.0057	0.0250	-0.23	0.819	-0.0547	0.0433

Table 3: Random Effects Regression Correlation Coefficients

Firm age does not seem to be of importance for the most patent innovative Swedish companies when controlling for all other factors in the more general random effects regression (see extended output in Appendix 11.2). This indicates that firm age is only a good predictor of patent innovation levels to the extent that it can help predict other relevant factors such as profits, revenues and company size. There does not seem to be any direct, significant knowledge accumulation within older companies that grows with age and helps stirr innovation. Instead, it appears that the creation of patents is similar to other types of productions in that it requires input such as capital and labor which is expected from a theoretical perspective, drawing parallels to the Solow model.

This is a particularly interesting result, and to the extent that smaller companies tend to be younger too as Klenow and Li reasoned, this goes against what is expected from OECD-data. If company age does not have an impact in and of itself, when controlling for other factors, this could indicate that young Swedish companies are not less inherently prone to turn to patenting than older ones. The fact that younger companies in the dataset also tend to be slightly less profitable, could point towards the fact that perhaps capital markets or other external financing alternatives do have some effect. Particularly, perhaps, for the youngest companies likely without substantial means of financing for research. The fundamental takeaway from analyzing firm age is thus that it matters to the extent that it can help predict other factors, but that it is insignificant in and of itself on a stand-alone basis.

Moreover, the fixed effects regression showed a positive correlation between profits and the number of patents registered per year, with 1.06 additional patents expected per year on average for every additional billion SEK in profits. The coefficient is lower in the general random effects regression, but still significant at a 95% significance level. This result provides several key insights on the relationship between profits and patent innovation levels among the most innovative Swedish firms, and allows for the possibility of some form of causal relationship between the two variables. The fact that profits have a positive effect that appears separated from both revenues and factors such as spending on research and amount of employees indicates that there is a unique relationship between patenting and profits. Considering this, what may the effect of profits be on patenting levels among companies?

Firstly, the positive coefficient for the profits variable may signify indirect effects over time. According to the existing literature, it is reasonable to expect research and development to lead to increased patenting among firms, which is also captured in the positive sign of the intangible assets variable. Simultaneously, existing literature indicates that in-house funds such as profits are used to finance spending on research and development, particularly among large companies. This could imply that there is an element of constraint in terms of resources that could affect small companies negatively. Firms with lower profits may not have sufficient funds to invest in the development of patents. In this way, the control factor for intangible assets may be used to infer something about the effect of profits. Companies with relatively high profits for the years 2010-2013 within the dataset may also have had high profits during previous years. These profits, particularly for larger companies, may have been used to also finance capitalized research expenditures for the analyzed years. In this way, which was also brought up as part of the research design, profit-levels across companies may not only have an effect in and of themselves but also indirectly through for example intangible assets over time. To fully understand the effects of profits, detailed analysis of the mechanics of how it helps finance research needs to be carried out. This, however, is outside the immediate scope of this research paper. Profits may have indirect effects channeled through control variables included over time, such as intangible assets, but exact relationships require further research.

Regardless, the fact that there exists a unique relationship between profits and the number of patents registered even when controlling for revenues, employees, intangible assets and other factors across companies, indicates that there is more to it. This effect could, at least in part, be a result of intangible assets not fully capturing all activities that help create patents. There may be other activities or expenses not captured in the model that, had they been controlled for, would have decreased the profits coefficient. Moreover, the coefficient for profits being positive when holding revenues fixed could indicate that profit margins play a certain role. Increased profits, holding sales fixed, would represent both increased actual profits but also increased margins. It may be the case that more cost effective companies are more efficient in their work, more determined or otherwise differently structured in their efforts with producing patents.

At the same time, it may also be merely a correlation to some degree. Perhaps companies with more patents generally obtain higher profits holding all other factors fixed. Or, perhaps, companies that are more cost-efficient also tend to be more active within patenting as a strategy to block competitors' research efforts. Similarly, the patent filing process and the protection of patents may be expensive. Companies with lower profits for the years in the dataset may thus be less inclined to engage in the process. Moreover, it is also possible for the relationship to be the other way around entirely. As Kiraci, Celikay and Celikay's research showed, research and development levels are associated with long-term profitability. Perhaps firms with high profit-margins and profits tend to have researched more in the years leading up to 2010 in a way that is not fully captured within the average intangible assets variable. Within the context of interpreting the importance of the positive relationship picked up by the profits variable, the size of the effect may also be relevant to analyze. While there appears to be a positive relationship, the expected increase in the number of patents registered relative to a given unit of profits is not particularly large. A large increase in the profits variable is needed for vast change in the number of patents registered. This may be due to the inclusion of control factors such as intangible assets or the number of employees. It is not possible to conclude with certainty in what ways profit-levels, when fixing other elements, interact with patenting, and to what extent this effect represents correlation or causality in part. However, profit-levels for the years 2010-2013 do have an explanatory value in regards to the number of patents registered on average and proves to act as a significant estimator within the fixed effects analysis.

Even though the unique relationship between profits and the number of patents registered per year across companies on average is not completely clear, profit is a statistically significant predictor even when controlling for differences across industries as well as time-trend effects. One assumption in how the model design was chosen was that there may have been residual effects from the financial crisis of 2008. However, when including year-dummies in the fixed effects regression, the following excerpt was presented as part of Table 1:

Independent Variables	Coefficient	Robust Standard Errors	t	$P >\mid t \mid$	95% Confidence Interval	
Year						
2011	0.8094	0.4306	1.88	0.068	-0.0624	1.6811
2012	1.3279	0.6805	1.95	0.058	-0.0497	2.7054
2013	1.0401	1.0541	0.99	0.330	-1.0938	3.1740

Table 4: Time-Trend in Fixed Effects Regression

There does not appear to be any significant year-to-year effects from a time-trend perspective at a 95% significance level. Considering this, it is still possible that omitted variable bias is reduced from the time trend being included, meaning any potential effects that differences in years have in and of itself are isolated from its effects on profits.

However, even though there are no significant time-trends in general, including a lagged profit variable in a fixed effects regression on the number of patents using only the profits variable provides some additional insights. On average, there seems to be a positive "last-years" effect for profits, where the previous years' profits levels have an effect on the expected number of patents registered on average (see Appendix section 11.3). This effect is relevant at a 95% significance level with a P-value of 0.000. One implication from this is that there is a time-dimension of when profits are generated in relation to when the patents are registered. This could imply that there, at least to some extent, exists some temporal interaction between profits and the creation of patents among Swedish top innovators. One implication is that profits may have an effect on the timing of registering patents. For example, having had a previously profitable year, companies may be more inclined or eager to register a patent. The exact mechanics of such a relationship are not straightforward within the context of the model used in this research paper. However, this adds to the fact that profit-levels in and of themselves relate to the number of patents created over time. While this may strictly be a correlation, it could also be that last year's profits affect activities outside the measurable scope of the model that help produce patents.

On the same topic, the patent application process could also be several years long in some cases, as discussed in section 5.1. Newly registered companies included in the dataset may not have amassed several profitable patents already in use. The fact that "last-years" profits are related to the number of patents registered for the dataset as a whole, while company age is not significant, may imply that profits play a role in creating patents. Another way this might be explained is that "last years" profits interact with some form of spending on research and development that could increase the number of patents registered. However, these relationships are not completely clear, and would also require further analysis beyond the immediate scope of this analysis and research paper.

8 Conclusions

The purpose of this research paper has been to widen the existing knowledge on the complex topic of patenting. Empirical work on the demographics of patenting internationally showed trends of larger, likely older and more profitable firms dominating within research and patenting, with smaller, likely younger and less profitable firms innovating in different ways. Sweden stands out in several ways from an international perspective. Relatively more is spent on research and development, young companies are described as very innovative and the capital markets appear particularly active. This made profits and firm age interesting areas of research in relation to patenting levels in Sweden. Accordingly, whether firm age and year-to-year profit-levels would matter for the number of patents registered per year during the period 2010-2013 among top patent innovators in Sweden became the question at hand. Using a dataset of 40 randomly selected firms with at least five patents registered during the period 2010-2013, our short time-series fixed effects empirical model has shown that while age is not an important factor in and of itself, profits have a statistically significant predictive effect in relation to the number of patents created.

The fact that age is not a significant predictor of patent innovation among the most innovative Swedish firms appears to go against international trends. Experience in terms of years since firm registration is not significant in and of itself, indicating that young Swedish firms are not less inclined to patent, when controlling for resources such as revenues and profits, than older, likely larger firms. At the same time, profits are of statistical significance in predicting patenting-levels among the most active Swedish patentors, even when controlling for revenues, number of employees, sector and firm differences, intangible assets, age and potential time trends. There also appears to be a "last-year's" effect for profits, with last year's profits being significantly correlated with the number of patents registered across companies. The ultimate conclusions that can be drawn from this however are less straight-forward.

Existing literature predicts there to be a relationship between profits and spending on research and development, and research and development and patenting in turn. Higher profits during 2010-2013 may correlate with long-term profitability, which may have affected spending on research and development in ways that are not measured through the econometric model. Moreover, profits being statistically significant may indicate that profit-margins matter too as an indicator of efficiency, or that all spending on research and development is not captured by intangible assets. Intangible assets being of statistical significance may also show that profits matter, to the extent that profits help finance research. The costs associated with the patent application and protection process may also matter. At the same time, the profits effect may also stem from patents being profitable. However, the extent to which this matters is unclear, since firm age is not a significant predictor with younger companies likely having fewer patents already registered. The expected additional number of patents registered per unit increase in profits is also quite small relative to overall profit levels among firms. All and all, profits appear to matter and be statistically relevant in predicting the number of patents registered on average among the companies in the dataset between 2010-2013, even though the exact mechanics of its effects need additional research.

These results provide several wider implications for future research as well as the current state of knowledge. The fact that age is not an important factor in and of itself implies that constraints on resources may be a driving force for differences in patenting-levels across firms rather than intangible experience. Simultaneously, it shows that younger, likely smaller businesses may be both aware of, and interested in, patenting. This may be particularly interesting for policy makers in designing incentives for future innovation initiatives. Moreover, it may also act as encouragement to management of younger firms. Furthermore, the fact that profit-levels matter and act as efficient predictors of patenting levels across firms may also further imply that resources play a role in the production of patents. At the same time, this relationship may also confirm that patenting is associated with profitability in Sweden too. These facts could also be of interest to both policy makers and management in deciding how to design incentives and allocate resources to stimulate profitability and growth in patentable innovation.

In terms of future inquiries, several additional areas may be of particular interest. Extending the repertoire of research into the exact relationships between profits and spending on research and development over time may add to the discussion of profits and patenting in Sweden. Including more years and companies within the analysis of patenting may also provide additional value to the existing research. Moreover, including other and more specific measurement variables for the spending on research and development could also potentially decrease omitted variable bias for the profit variable and may thus be of value. Lastly, including more qualitative inputs from companies through for example interviews or similar measures may also provide some further insight into the quantitative analysis and the mechanics of key variables.

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10 Appendix

10.1 Econometric Model Variables and Description

Variable	Description
Pat	Numerical variable, representing number of patents registered of a company. The variable data was extracted from the Patlink database.
Prof	Numerical variable, representing the firm profits. The variable data for this variable was extracted from the variable resar (Åretsresultat) in the serrano database.
Rev	Numerical variable, representing the firm revenue. The variable data for this variable was extracted from the variable ntoms (Nettomsättning) in the serrano database.
RegYr	Numerical variable, representing the firm's registration year. The variable data for this variable was extracted from the variable ser_regdat (Registreringsdatum) in the serrano database.
NumEmp	Numerical variable, representing the firm's number of employees. The variable data for this variable was extracted from the variable antanst (Antal anställda) in the serrano database.
IntA	Numerical variable, representing the firm's intangible assets. The variable data for this variable was extracted from the variable imanlsu (Immateriella anläggningstillgångar) in the serrano database.
AvgIntA	Numerical variable, representing the firm's 5 yr. Avg. Intangible Assets. The five-year average of the intangible assets five years before 2010. The data was extracted from the variable imanlsu in the serrano database.
EngyEnv	Dummy variable, which tells if the company belongs to the sector Energy & Environment. The data was extracted from the variable bransch_borsbransch_konv (Branschsektor).
Mat	Dummy variable, which tells if the company belongs to the sector Material. The data was extracted from the variable bransch_borsbransch_konv (Branschsektor).
IndstG	Dummy variable which tells if the company belongs to the sector Industrial goods. The data was extracted from the variable bransch_borsbransch_konv (Branschsektor).
ShopG	Dummy variable which tells if the company belongs to the sector Shopping goods. The data was extracted from the variable bransch_borsbransch_konv (Branschsektor).
HthEd	Dummy variable which tells if the company belongs to the sector Healthcare and Education. The data was extracted from the variable bransch_borsbransch_konv (Branschsektor).
ITElec	Dummy variable which tells if the company belongs to the sector IT & Electronics. The data was extracted from the variable bransch_borsbransch_konv (Branschsektor).
CorpServ	Dummy variable which tells if the company belongs to the sector Corporate Service. The data was extracted from the variable bransch_borsbransch_konv (Branschsektor).

For the variables that varied at the company level, we used the financial statements at the group level to extract the data. Group-level financial data was selected by filtering by the variable K in the Serrano Database mainly due to the availability of the data. Having the group level data also gives a wider representation of what contributes to the value creation of patents and how they interact with various variables.

10.2 Random Effects General Regression

Number of Observations	136
Number of Groups	36
R^2	
Within	0.3906
Between	0.6774
Overall	0.5226

Independent Variable	Coefficient	Robust Standard Errors	t	$P >\| t \|$	95% Confidence Interval	
Profits (per Billion SEK)	0.663	0.133	5.00	0.000	0.404	0.923
Revenue (per Billion SEK)	1.40	0.454	3.09	0.002	0.513	2.29
Intangible Assets (per Billion SEK)	1.36	0.617	2.20	0.028	0.150	2.57
5 Yr. Avg. Intangible Assets (per Billion SEK)	-12.2	2.54	-4.80	0.000	-17.2	-7.22
Registration Year	-0.0057	0.0250	-0.23	0.819	-0.0547	0.0433
Number of Employees	0.0017	0.0017	1.03	0.303	-0.0016	0.0051
Energy & Environment	3.1046	2.1355	1.45	0.146	-1.0810	7.2903
Materials	3.1227	2.7549	1.13	0.257	-2.2767	8.5222
Industrial Goods	2.7789	2.0049	1.39	0.166	-1.1506	6.7084
Shopping Goods	0.1713	1.8465	0.09	0.926	-3.4477	3.7903
Convenience Goods	0	(omitted)				
Healthcare & Education	1.3206	2.0759	0.64	0.525	-2.7481	5.3892
IT & Electronics	2.5362	2.0254	1.25	0.211	-1.4336	6.5060
Corporate Service	3.6055	2.3401	1.54	0.123	-0.9810	8.1920
Constant	10.6274	49.1902	0.22	0.829	-85.7835	107.0384
σ_u	1.2122					
σ_e	2.9053					
ρ	0.1483	(Fraction of variance due to u_i)				

Table 5: Random Effects general regression

10.3 Lagged Profits Fixed Effects Regression (with Robust SE)

Number of Observations	113
Number of Groups	39
R^2	
Within	0.2263
Between	0.0626
Overall	0.0608

Independent Variable	Coefficient	Robust Standard Errors	t	$P >\| t \|$	95% Confidence Interval	
Profits (per Billion SEK)						
	-0.195	0.149	-1.31	0.198	-0.496	0.106
Lag weight	1.42	0.116	12.24	0.000	1.19	1.66
Constant	1.8425	0.0180	102.54	0.000	1.8061	1.8789
σ_u	5.4828					
σ_e	3.1029					
ρ	0.7574	(Fraction of variance due to u_i)				

Table 6: Lagged Profits Fixed Effects regression (with Robust SE)

10.4 General Terms for Usage of Data

There are several terms and conditions stipulated for the usage of both the Serrano and the PAtLink databases. The Swedish House of Finance and its licensors “have and shall retain, all title, exclusive ownership rights and all intellectual property rights and other rights and interest in the Service and the Data.”. As part of this paper, it is recognized that the data has been “prepared, selected, coordinated and arranged through the expenditure of substantial time, judgement and money and constitutes valuable property of SHoF and its licensors”. Furthermore, it is also noted what responsibility is necessary to take on in the case of potential harm caused by this report and the usage of the data. For the purposes of this research paper, our usage of the data should be accepted and in accordance with various stipulations, contingent on that this paper gets submitted to datareport@houseoffinance.se in accordance with their stated guidelines should it be published or otherwise be made publicly available.[75]

[75] Swedish House of Finance, Terms and Conditions, 2021