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The Impact of Technological Innovation on Financial Performance: an Empirical Study on S&P 500 Firms

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Abstract

This study explores the impact of technological innovation on financial performance among S&P 500 firms, focusing on R&D intensity and the number of patents. The key indicator adopted as a measure of firms' performance is Tobin's Q, which is found to be positively correlated with R&D intensity. Surprisingly, a negative correlation is shown between Tobin's Q and the number of granted patents, possibly due to inefficiencies in managing large patent portfolios or prioritizing patent quantity over quality, suggesting that solely increasing the patent count is likely to reduce profitability. These findings provide valuable insights into how innovation can drive financial success and highlight the necessity of a balanced innovation strategy to achieve long-term profitability and competitive advantage.

Introduction

In modern times, the rapid pace of technological advancement has radically changed the business world and innovation is now crucial for both achieving economic growth and gaining a competitive advantage. Therefore, understanding the impact of innovation on financial performance is key to achieving business success. However, the association between innovation and performance can be intricate and multifaceted. This study aims to explore this relationship through a comprehensive empirical analysis of firms within the S&P 500 index. This sample includes 500 of the largest listed firms in the United States, that are also some of the biggest companies globally and often leaders in their respective industries and pioneers in the adoption and development of innovations, making them ideal subjects for the analysis.

It has been acknowledged that innovation plays a critical role in promoting economic growth and company success since Schumpeter's concept of "creative destruction". The theory strongly emphasises the substantial impact of innovation, which is necessary for technological advancement. In today's world, the ability to innovate has become even more critical, as innovative firms are far more likely to disrupt the market and become leaders or obtain a strong competitive advantage. Newer theories and research acknowledged the theoretical benefits of innovation, additional empirical examination is required to assess its specific effect on firm performance.

This research seeks to investigate the impact of R&D intensity and patenting activity on firm valuation and performance using Tobin's Q as the dependent variable. This metric measures the market value of a company in relation to its asset replacement cost and is widely regarded as a forward-looking indicator of financial health. The analysis takes into account a range of financial metrics from the last years, used as control variables, and time-specific and sector-specific factors to provide more accurate results.

To sum up, this study aims to contribute to the growing literature on innovation through a detailed empirical investigation of S&P 500 companies. By examining this relationship, this research intends to offer insights for both scholars and corporations by highlighting the critical role of technological innovation in achieving long-term and sustainable financial success.

Literature Review and Hypotheses

3.1 Historical view

Historically, technological innovations marked a major turning point in the way firms operate. The Industrial Revolution is one major evidence of the impact that technological advancement had on firms, as it completely transformed both the way goods were manufactured and the role of labour. The creation of new types of machinery and production processes led to an increased level of productivity, efficiency, and, consequently, profits. Thus, it became evident that the role that innovations play in shaping the evolution of firms is central. Joseph Schumpeter, one of the most important and influential economists of the last century, noticed this correlation, especially regarding the role of innovation. The Austrian, who can be acknowledged as the first forerunner of innovation, identified innovation as a fundamental driver of economic progress (Pol and Carroll 2006).

The Austrian economist's theory is mainly focused on the concept of "creative destruction" (Schumpeter 1943). Schumpeter firmly believed that innovation is the engine of economic progress since it results in the creation of new products, services, and processes that create wealth. Its creative destruction theory is based on the idea that radical changes coming from entrepreneurial activities are what propels economic growth and disrupt the existing market structures to establish new ones (Schumpeter 1934). According to it, the disruption brought by new innovations leads to the obsolescence of previous technologies, severely damaging the incumbents. However, he argued that this mechanism is essential for technological advancement and efficiency enhancement, and thus for long-term economic growth (Schumpeter 1943). He also identified entrepreneurs as catalysts for this creative destruction process, since their role is key to disrupt the market with new innovations (Schumpeter 1939). Schumpeter distinguished five types of innovation (Śledzik 2013):

1. introduction of a new product or a new version of an existing one;
2. implementation of new techniques of production or sales of a product;
3. creation of a new market;
4. access to new sources of raw material or semi-finished goods;
5. creation of new market structures.

In the following years, scholars made another distinction by introducing the concepts of radical and incremental innovation. The former refers to significant technological or business model changes that completely disrupt the market and that typically guarantee high rewards and have long-term impacts; the latter, instead, refers to gradual and small improvements to existing products or processes, enhancing their performance but providing the firm with lower rewards than the other innovation type (Henderson and Clark 1990; Dewar and Dutton 1986). Even though the word "innovation" was already used in some reports at the end of the 19th century, Schumpeter can be easily defined as the initiator of innovation theory (Śledzik 2013). Since him, indeed, researchers have started to argue that technological innovation plays a fundamental role in economic growth and creative destruction is the key driver of real income per capita great increase in Western industrialized economies (Kogan et al. 2012; Scherer 2007).

After Schumpeter, one of the most influential economists regarding innovation theories was Everett M. Rogers. The American is renowned for the creation in 1962 of the diffusion of innovation theory. Through it, he examines the process by which new ideas or technologies spread through certain communication channels over time across social systems (Rogers 1962). In particular, some factors have been recognized as crucial in influencing the diffusion of a technology: the relative advantage, compatibility, complexity, trialability, and observability. In his theory, Rogers developed the so-called Rogers bell curve, a model that distinguishes adopters of innovations into five different types, introducing for the first time the concept of "early adopter" (Rogers 1962). In the diffusion process, early adopters play a central function, since they are respected opinion leaders within their social system, and their adoption of the new innovation grants social validation. Thus, they bridge the gap between innovators and early adopters by sharing their experience with the innovation and its benefits. Furthermore, Rogers identified the critical role of communication channels (Rogers 1962). Through them, companies are able to create awareness and persuasion, while also influencing others' attitudes towards the innovation thanks to opinion leaders (Valente 1996. The theory has been empirically supported and later adapted to modern technology where the main communication channels became digital platforms and social media and the spread of innovations highly accelerated (Brossard 2013; Wejnert 2002).

During the early 2000s, a new idea regarding innovation in organizations was introduced by the American economist Chesbrough (2003), as he challenged the traditional closed model with the new concept of open innovation. This term refers to a new approach that involves leveraging external ideas, technologies, and expertise to promote firms' innovation. Chesbrough's idea came as a solution to the increasing costs and complexity of innovation and to other factors that made the old model inefficient. With the traditional approach, indeed, companies only relied on their internal R&D to pursue innovation. Instead, open innovation allows firms to improve their efficiency and effectiveness by shortening development cycles, reducing costs related to innovation, and reducing risks associated with it (Maxwell 2006; Greco, Grimaldi, and Cricelli 2018). Companies can use several methods to access external resources: strategic alliances, licensing agreements, joint ventures, or collaborative research (Gassmann, Enkel, and Chesbrough 2010). Moreover, open innovation impacts also the market environment and the corporates' structure and culture, making them more prepared and ready to deal with rapidly changing technologies and market dynamics. Such advantages are crucial in sectors where technological innovations are rapid and frequent and customer needs and tastes change a lot. Several studies agree that open innovation strategies positively impact companies' performance by boosting growth and business development and possibly granting a competitive advantage (Greco, Grimaldi, and Cricelli 2016; Bigliardi et al. 2020).

According to this new idea of looking outside of the organization, during the last two decades a new concept gained a foothold: innovation ecosystems. The term was first introduced by Moore (1999), who described it as "an economic community supported by a foundation of interacting organizations and individuals", highlighting the interconnectedness and interdependence of innovation activities within a network of different participants. As said, this paradigm became popular in the late 2000s, where it has been defined as an evolving set of actors, comprising firms, universities, research institutions, government agencies, investors, and intermediaries, who interact and cooperate to develop new technologies (Adner 2006). This approach comes from the recognition that innovation is gradually becoming more and more reliant on the collective efforts and synergies of different players. These ecosystems work as ground for the proliferation of ideas and greatly contribute to fostering innovation (Valkokari 2015). Especially thanks to digital transformation, ecosystems have now reached a global dimension, meaning that companies can access resources and knowledge at a global scale, increasing even more their potential. Thanks to new technologies, the number of opportunities for innovation increased as firms can more easily obtain and manage vast amounts of data that were before unattainable (Nambisan et al. 2017). In addition to the performance-enhancing effects already mentioned, strong ecosystems greatly increase the resilience of their firms against disruptions such as economic crises, making them more capable of adapting and recovering. Thus, innovation ecosystems are a great resource for firms to further foster innovation and long-term performance (Autio and Thomas 2014).

One of the latest technologies that is revolutionizing and completely changing how companies operate is Artificial Intelligence, which can be defined as machine learning that can sense, reason, act, and adapt based on experience with the scope of contributing to economic growth and improving people's standards of living (Kun-Hsing, Beam, and Kohane 2018). The impact of this new technology on companies has been extraordinary as AI can analyze complex data and extract meaningful relationships in datasets and perform other tasks that need human intellect (Morandín-Ahuerma 2022; Segato et al. 2020). Its impact is so significant that more than 80% of firms considers AI as a strategic opportunity and almost 85% sees it as a way to achieve competitive advantage (Enholm et al. 2021). Researchers widely agree that artificial intelligence has enormous potential for businesses and can provide them with several advantages (Tomaev et al. 2020; Enholm et al. 2021). Considering that AI can be included in a large number of business activities, its impact on companies is significant and multifaceted. In fact, it may be utilized to streamline operations and automate repetitive jobs, increasing operational effectiveness and cutting expenses(Ivanov, Dolgui, and Sokolov 2018). AI created an immense number of opportunities, with the possibility of firms even disrupting their market with the right innovation. With the unique capabilities obtained, companies have the opportunity to sharply increase their competitive advantage. By applying this technology to customer services, companies may obtain a productivity boost up to 45 percent of current costs (Chui et al. 2023). Different studies showed that firms adopting AI are more likely to achieve better financial results and become market leaders (Chintalapati and Pandey 2021; Ransbotham et al. 2018).It is then undoubtful that AI will play a big role for firms in the upcoming years.

Innovation is a very complex yet critical matter for a company and understanding the various factors that affect the innovation process is fundamental. The ability to innovate in a firm is influenced not only by internal elements but also by variables coming from outside of the organization. Regarding internal factors, it is fundamental for a firm to be able to attract and retain talent, as the individual ability to think creatively and solve problems is crucial to promote innovation (Brynjolfsson and Mcafee 2014).This is also further promoted by the corporate culture and environment (Amabile et al. 2018). Companies' innovation capabilities and development of ideas and technologies can be significantly boosted by adopting a culture that encourages creativity and risk-taking and that tolerates failure (Tidd and Bessant 2021). In this regard, firms can also change their organizational structure to foster innovation. A structure with decentralized decision-making and cross-functional teams can empower employees and promote collaboration and communication, facilitating the sharing of opinions and perspectives and the development of innovative ideas (Sinek 2017). Furthermore, the availability of resources of the company, especially from a financial perspective, is fundamental for experimentation and risk-taking during the research of new technologies. With a large capital and bigger expenditures in R&D, companies are more likely to invest in innovation, as they can have access to more advanced resources and technology as well as more skilled employees (Thornhill 2006).

Regarding external factors, the institutional environment greatly affects innovation, as well-functioning institutions, such as a good educational system or strong financial markets, can offer the resources, capital, and expertise support required (North 1990). The social environment shapes innovation as well, as it can promote risk-taking attitudes and creativity. Another critical element is the competitive landscape. With intense competition, innovation is crucial for a company to survive and differentiate to obtain a competitive advantage, pushing the firm to continuously innovate (Porter and Heppelmann 2014). Moreover, the geographic location of the firm is another external factor that affects its ability to innovate. Being part of a cluster or innovation ecosystem, such as the Silicon Valley region, can severely boost companies' innovation abilities as they can provide numerous and different supportive resources as well as great knowledge sharing (Kapetaniou, Samdanis, and Lee 2018). Regarding the company's location, the regulatory environment also plays a big role in incentivizing innovation. Tax incentives in R&D, funds for innovation hubs, or protection of intellectual property are all elements that support innovative companies, whereas adverse regulations can severely limit and slow their innovation process. Furthermore, the importance of being an innovative company and continuously introducing new technologies or products is dependent on the industry in which the firm is operating (Malerba and Adams 2014). Firms in industries such as technology, automotive, healthcare, finance, and energy heavily rely on their abilities to innovate and are required to invest more in R&D.

3.2 Patents

One of the main outputs of the innovation activities of a firm are patents. According to the WIPO (2024), a patent is defined as "an exclusive right, granted for an invention, which is a product or a process that provides, in general, a new way of doing something, or offers a new technical solution to a problem". By this definition, when a patent is granted, its owner gains an exclusive right, through which he can prevent others from making, using, selling, or distributing the patented invention without permission. In that sense, creating a big and wide patent portfolio can give a significant competitive advantage to a firm, as it prevents others from using similar technologies or processes. Nevertheless, the patenting process might be long and complex. First, a patent application with a detailed description of the invention must be submitted to the relevant patent office and, after 18 months, the application is published (USPTO 2024). The patent publication serves to inform the public about the existence of the innovation and possibly inform third parties whether they might be violating any potential future rights. However, it still does not provide any enforceable claims. Indeed, they are given to the inventor only when the patent is granted after passing the formal examination process. A granted patent, other than providing enforceable rights, gives its owner the possibility to monetize it through licensing, sale, or litigation. Having a large patent portfolio positively affects firm performance and provides several benefits to the company (Neuhäusler et al. 2011). From a strategic perspective, large patent portfolios create strong entry barriers, discouraging potential competitors from entering the market, but they also protect the market shares from the existing ones (Blind, Cremers, and Mueller 2009).

Moreover, patents serve as valuable assets. Not only do they contribute to increasing the company valuation, but they also attract new investments as they signal to investors that the company is able to create new and valuable ideas and investing in it is an appealing opportunity (Blind et al. 2006). Consequently, this can facilitate access to funding and partnerships necessary for further research and development. Additionally, patents can generate other revenue streams by establishing licensing agreements with other firms in order for them to be able to access the patented technology or process. Therefore, patents significantly increase a company's bargaining power, allowing it to dictate the terms of the agreement, negotiate better deals, and potentially secure strategic partnerships. Patents' role in encouraging innovation is critical. Given the several advantages gained by obtaining a patent, firms are highly incentivized to invest in research and development. In this competitive environment, companies usually engage in so-called "patent races" to ensure the grant of the patent, resulting in a great effort in innovation. Also, winning these patent races affects a company's follow-on innovation, both in direction and magnitude (Blind et al. 2006), further promoting innovation. Such an innovative environment not only benefits companies, which gain from newer and better products or services or more efficient processes, but also customers and the economy in general, as knowledge

sharing and technologic transfer are promoted, enabling open innovation and collaboration and encouraging companies partnerships (Trippe 2022).
Considering the above, it is still necessary to assess their financial impact on corporations. The relation between patents and their impacts on financial performance is complex. Indeed, it strongly depends on the industry and the technological importance and disruption of the innovation. In general, studies agree that patents have a positive influence on financial performance (Alt 2018; Neuhäusler et al. 2011), especially in industries with cheap imitation and where the R&D process is capital-intensive and uncertain (Orsenigo, Sterzi, et al. 2010).

3.3 Research Gap and Questions

To evaluate the effects of innovation on company performance, scholars used various indicators. However, it has been widely recognised that one of the most suitable indicators for this purpose is Tobin's Q (Singhal, Fu, and Parkash 2016; Anderson, Fornell, and Mazvancheryl 2004). Tobin's Q is a measure conceived by the economists Kaldor and Tobin in the late 1960s and early 1970s (Kaldor 1966; Tobin 1969). It is defined as the ratio between the market capitalization of a firm and its total assets replacement cost. Since estimating the replacement cost of assets can be challenging and not precise, there are different ways to calculate the ratio. This analysis implements the formula employed by the Orbis Database to calculate Tobin's Q, which is the following:

$$\text{Tobin's Q} = \frac{\text{Market Capitalization}}{\text{Total Assets}}$$

Tobin's Q is commonly utilized because it is comparable across multiple industries and is forward-looking, as it contains an assessment of a company's future performance based on current technological activities (Anderson, Fornell, and Mazvancheryl 2004). Since such an assessment is provided by stock markets, this ratio is a suitable indicator only for listed firms on well-functioning stock markets, which is the case with the sample used in this analysis (Belderbos et al. 2010). This forward-looking aspect is important since results from technological activities often manifest only several years after the activities have taken place (Czarnitzki, Hall, Oriani, et al. 2006). Values higher than 1 indicate that the market value is greater than replacement costs, suggesting expectations of good future performance; conversely, a value lower than 1 might suggest inefficiencies in the company and potentially worse future performance.

Several studies explored the connection between investments in R&D and company evaluation. They argue that investments in R&D boost future profits thanks to the creation of intangible assets that increase market valuation (Pramod, Krishnan, and Puja 2012). In 1993, Chauvin and Hirschey (1993) analysed more than 1,500 firms from 1988 through 1990 and found a positive correlation between R&D expenditure and firms' Tobin's Q. With the study "Firm size and the effect of R&D on Tobin's q", Connolly and Hirschey (2005) obtained the same results with a larger data sample covering 5 years and 3,100 companies. Later, an analysis by Bardhan, Krishnan, and Lin (2013) on S&P 500 firms from 1997 to 2004 confirmed again this positive correlation. During the last years, other studies further confirmed this positive correlation between higher R&D spendings and Tobin's Q (Rahman and Howlader 2022; Patin, Rahman, and Roach 2024). Some researchers measured the R&D efforts of companies using R&D intensity as independent variable. R&D intensity is the ratio between a firm's R&D expenditures and its total sales and shows the percentage of the revenues that is reinvested in R&D. This indicator is useful to compare companies with different sizes and may better reflect the efficiency and effectiveness used R&D intensity (Belderbos et al. 2010; Pramod, Krishnan, and Puja 2012). A study by Belderbos et al. (2010) on a panel dataset with R&D-intensive firms from 1996 to 2003 implemented R&D intensity, calculated as ratio between R&D expenditures and total assets, as a control variable, finding a positive significant correlation with Tobin's Q. In 2012, an analysis on manufacturing firms in India again proved this correlation to be positive. Based on these arguments, this analysis expects to obtain similar results, formulating the follwing hypothesis.

Hypothesis 1: R&D intensity positively influences Tobin's Q

Moreover, past literature also examined the connection between patents and Tobin's Q. This relationship is very complex and there are several indicators to be used regarding firms' intangible capital and patent portfolio. Previous research shows a great correlation between market valuation and patent performance (Hirschey and Richardson 2004; Chen and Chang 2009). It has been observed that, since patents are one of the main outputs of firms' innovation activities, they serve as signals of how well they are performing in stock markets (Chen and Shih 2011). Megna and Klock (1993) calculated a firm's patent stock as the weighted sum of current and past granted patents, concluding that intangible capital significantly affects Tobin's Q. A 2011's study analysed this topic using the ratio between patent count and sales and discovered a positive correlation with Tobin's Q (Chen and Shih 2011). Another study that considered patent citations count as the explanatory variable found a positive correlation (Chin et al. 2006). However, Neuhäusler et al. (2011) implemented different patent activity indicators and concluded that the number of patent applications does not well predict firm performance. Other research observed a significant, although very minor, negative correlation between patents count and Tobin's Q (Grigaitis 2016). Previous literature showed mixed results regarding the correlation between patent activity and firms' performance, therefore this analysis aims to further investigate this topic using the number of patents granted per year as a variable, formulating the following hypotheses:

Hypothesis 2: A higher number of patents granted positively influences Tobin's Q

In summary, this study aims to fill the gap in research on the combined impact of innovation and patenting activities on a company's financial performance. Although previous studies have already found that the impact of R&D is positive, this research aims to contribute to the literature by using R&D intensity as an explanatory variable to measure innovation effort and the number of granted patents as explanatory variables to measure patent activities output. Although few studies have used R&D intensity as a variable, the gap is particularly relevant for large, publicly traded companies. Moreover, there is still no clarity in the literature regarding the impact of patent activities on financial performance, so this study attempts to contribute by exploring for the first time the impact of the number of granted patents.

Methodology

4.1 Dataset

To conduct the empirical analysis, the firms included in the Standard&Poor 500 index were selected as population. A panel dataset containing firm-specific data of 500 companies of the period extended from 2018 to 2023 was built. The selected firms were those included in the index in 2024. Besides those about patents, all the data were collected from Bureau van Dijk's Orbis database. All monetary variables used are measured in USD dollars. The data related to patents were collected from World Intellectual Property Organization's PATENTSCOPE database. Unfortunately, companies do not always disclose their data about R&D expenditures, so firms with this observation missing were excluded from the sample. A small number of firms was excluded due to their lack of information about Tobin's Q. Thus, the sample size was reduced to 208 firms from the starting 500, obtaining a total of 1,248 observations.
There are numerous reasons why S&P 500 firms have been selected as population for this study. The S&P 500 index includes 500 of the largest firms listed on stock exchanges in the U.S. These companies are among the biggest and most influential firms globally and their activities significantly impact the world economy and financial markets. Several of them are innovation leaders and early adopters of new technologies, thus possibly providing useful information about R&D practices and their effectiveness, and have large patent portfolios, making it easier to analyse patent impacts. Moreover, S&P 500 firms have strict financial disclosure requirements, meaning that detailed, high-quality, and accurate data are available. S&P 500 companies also are more financially stable than small companies, reducing the variability of external factors in the analysis, and belong to a varied number of sectors, granting a diverse population and the possibility of examining diversities and similarities in innovation between different industries. Table 6 shows the sample distribution by sector using SIC codes. The dataset encompasses several different industries, but the vast majority of the companies come from manufacturing-related sectors. This reflects the fact that these are sectors in which the competitive advantage lies in the ability to frequently introduce and develop new innovative products and capabilities and therefore require large R&D investments. Conversely, it might reflect the case of firms that reach higher efficiency through process innovation, which requires significant R&D investments as well. To have larger and more valuable groups for analysis, the companies are grouped according to the classification in table 1.

Table 1: Reclassification of Sector Groups

Code	Sector	No. of firms	No.of obs.
A	Chemicals and allied products manufacturing	29	174
B	Industry machinery and equipment manufacturing	18	108
C	Electronic and other electric equipment manufacturing	27	162
D	Transportation equipment manufacturing	16	96
E	Instruments and other related products manufacturing	31	186
F	Other manufacturing activities	31	186
G	Services	37	222
H	Others	19	114

4.2 Variables selection

According to the previous examination, this section aims to determine and finalize which variables are used in the analysis of the impact of R&D and patents count on firms' performance.

Dependent variable

The dependent variable that will be used in the model is Tobin's Q. As said in the previous section, it is measured as the ratio between its market capitalization and its total assets. Since the sample includes only listed companies, it is an appropriate indicator to measure financial performance.

Independent variables

The analysis implements two different independent variables to explore their effects on the dependent variable. The first independent variable used is R&D Intensity, which is calculated by dividing R&D expenditure by total sales and that quantifies the percentage of revenues reinvested in R&D activities by the firm. It is an indicator of how much a firm prioritizes innovation in relation to its sales volume and a high value might suggest the potential for future growth, possibly attracting investors.

The second independent variable is the number of granted patents. It specifies the number of patents that have been examined by a patent office and legally recognized as intellectual property rights in a given year. A high value can boost a firm valuation due to the full protection of the intellectual property, while also directly contributing to revenues thanks to direct exploitation or licensing.

Control variables

Control variables are used to adjust for the influence of other factors on the relationship between dependent and independent variables, making the analysis more accurate and reducing bias. In the analysis, the following control variables are used:

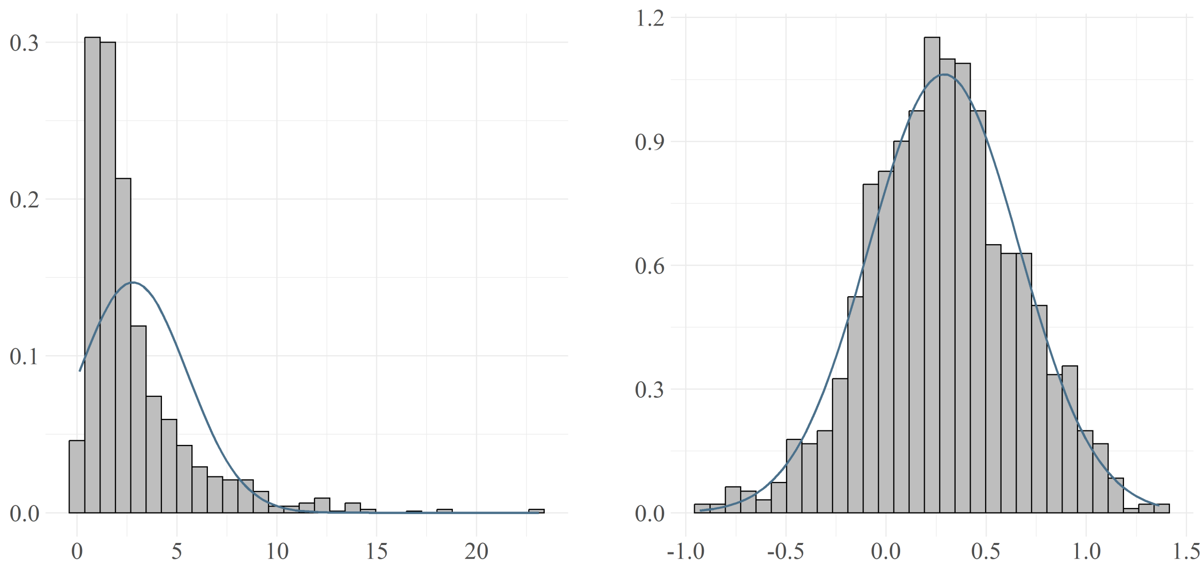
- *Total assets*: an indicator of a company's resources and scale. Higher numbers can imply higher operational capabilities and support for intensive R&D strategies.
- *Total intangible assets*: the total number of non-physical assets such as patents, trademarks, and goodwill. Higher values, especially in knowledge-driven industries, can suggest an effective innovation strategy, which may be reflected in the market valuation.
- *Total sales*: the direct measure of a company's performance and ability to generate revenues. Higher values can indicate operational success and can improve the company's perception of sustainable profitability.
- *Number of employees*: the scale of the workforce. A larger number may suggest greater R&D capabilities and innovative outputs, but also involves higher operational costs.
- *Firm age*: this number can be a proxy for experience, resilience, and a more varied portfolio of products, which can be reflected in the market valuation.
- *Net income*: directly measures profitability and a firm's ability to generate profits. Higher values increase investors' confidence and consequently firms' valuation.

The analysis takes into account time and sector as fixed-effects to provide more robust results. Time fixed-effects control external variables, such as macroeconomic trends and economic cycles, that uniformly affect all firms, while sector fixed-effects control encompasses industry-specific effects that might affect firms' results.

4.3 Method

The method implemented to examine the relationship between the selected variables in this study is the regression analysis and, specifically, the Ordinary Least Squares method. Moreover, to prevent the results from being skewed by transitory economic conditions or sector-specific characteristics, the model includes time and sector-fixed effects. By incorporating these fixed effects with the OLS method, which is an approach particularly valuable with panel datasets, the findings of the analysis are more robust and accurate. Previous researchers used both Tobin's Q and its logged value to run it as the dependent variable. Figure 1 shows the skewness of Tobin's Q value before (2.552) and after (-0.066) being logarithmic transformed.

Figure 1: Skewness of Tobin's Q and its logged value



(a) Tobin's Q

(b) Logged Tobin's Q

Using a logarithmic transformation helps to reduce the skewness and stabilize variance. That way, the distribution is closer to normal and fulfills OLS model assumptions. Thus, to obtain a better model fit and more robust results, this study uses Tobin's Q logged value. For more accurate results, some other variables have been transformed as explained in 4. The regression analysis is run using RStudio with the 'lm' function. The equation implemented in this analysis is the following:

$$\begin{aligned}\text{Tobin's Q}_{it} = \beta_0 &+ \beta_1 \text{R\&DIntensity}_{i,t} + \beta_2 \text{GrantedPatents}_{i,t} \\ &+ \beta_3 \text{TotalAssets}_{i,t} + \beta_4 \text{TotalIntangbile}_{i,t} + \beta_5 \text{TotalSales}_{i,t} \\ &+ \beta_6 \text{Employees}_{i,t} + \beta_7 \text{FirmAge}_{i,t} + \beta_8 \text{NetIncome}_{i,t} + \\ &+ \delta_t \text{Year}_t + \gamma_j \text{Sector}_j + \varepsilon_{it} \end{aligned} \tag{4.1}$$

Where:

- Tobin's Q_{it}: Dependent variable indicating the value of Tobin's Q.
- β_0: Intercept term.
- $\text{R\&DIntensity}_{i,t}$: Independent variable representing the ratio between R&D expenditures and total sales.
- $\text{GrantedPatents}_{i,t}$: Independent variable representing the number of granted patents.
- TotalAssets_{it}: control variable representing total assets.
- $\text{TotalIntangbile}_{it}$: control variable representing total intangible assets.
- TotalSales_{it}: control variable representing total sales.
- Employees_{it}: control variable representing the number of employees.
- FirmAge_{it}: control variable representing the years passed from foundation.
- NetIncome_{it}: control variable representing net income.
- $\delta_t \text{Year}_t$: Time fixed effects, where δ_t are the coefficients for each year dummy variable Year_t.
- $\gamma_j \text{Sector}_j$: Sector fixed effects, where γ_j are the coefficients for each sector dummy variable Sector_j.
- ε_{it}: Error term capturing unobserved factors affecting firm growth.

Results

5.1 Descriptive Statistics

Table 2 presents the descriptive statistics of the dependent variable for each year under consideration. The table shows the descriptive statistics of the dependent variable for each year under consideration. The average Tobin's Q increased from 2.311 in 2018 to 2.827 in 2023, revealing a general upward trend.

Table 2: Tobin's Q Statistics from 2018 to 2023

Year	Mean	Std. Dev.	Median	Min.	Max.
2018	2.311	1.892	0.975	0.117	10.434
2019	2.608	2.254	1.02	0.14	12.224
2020	3.112	3.185	1.078	0.129	18.583
2021	3.396	3.418	1.239	0.317	22.909
2022	2.559	2.258	1.149	0.18	12.565
2023	2.827	2.828	1.103	0.175	23.121

Table 3: Dataset Descriptive Statistics

Variable	Mean	Std. Dev.	Median	Min.	Max.
$R\&DIntensity$	9.111%	26.770%	5.232%	0%	824.310%
$GrantedPatents$	400.481	874.621	101	0	9,598
$PublishedPatents$	801.229	1,658.077	221.5	0	18,790
$TotalAssets$	44,621,605.641	73,528,689.924	18,815,113.5	339,937	551,669,000
$IntangibleAssets$	12,687,465.284	24,538,599.742	4,290,850	0	310,197,000
$Sales$	27,406,860.012	54,062,546.802	10,419,647	60,209	574,785,000
$NumberofEmployees$	50,255.732	108,627.331	19,300	274	1,608,000
$FirmAge$	47.433	37.849	32	1	141
$NetIncome$	3,285,139.056	9,014,453.229	1,072,400	-23,276,000	99,803,000
$GrantedPatentsPropensity$	0.040%	0.058%	0.021%	0%	0.533%
$PublishedPatentsPropensity$	0.085%	0.122%	0.044%	0%	1.1094%

This suggests that throughout time, the market valuation of companies relative to their assets is generally increasing. The median values are lower than the means for each year, denoting

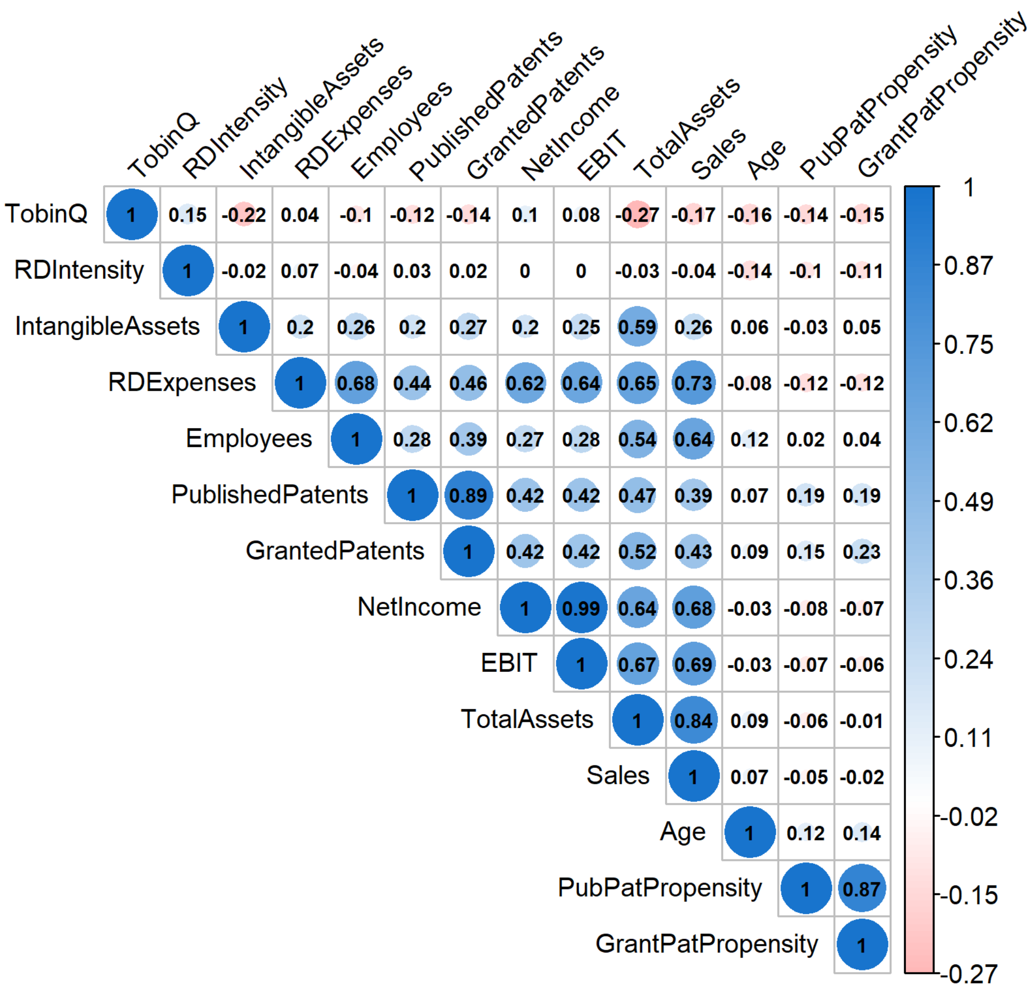
a right-skewed distribution. Moreover, there are significant variations in the standard deviation, especially in 2021, where it shows the highest variability, indicating that in that year there was more dispersion of Tobin's Q across companies.
Table 3 shows an overview of the descriptive statistics of every variable used in the dataset. It is possible to observe a wide range of R&D investments across firms, with a maximum value in R&D intensity of 824.31%, while in some years some firms showed a value of 0%. It is also possible to notice a great variability in patent activity, with some firms publishing or having granted no patents in some years, while others showed substantial numbers, such as 9,598 and 18,790 in granted and published patents respectively. In these variables, the medians are much lower, denoting a skewed distribution where some firms own very large patent portfolios.

5.2 Multicollinearity

To develop the analysis, in addition to the main variables, company variables are selected regarding their size and capacity, financial performance, and innovativeness. To avoid multicollinearity issues, a visual representation of the correlation between the different variables is provided in Figure 2. The plot displays the Pearson correlation coefficients, which can assume values ranging from -1 to 1. Values around zero denote no association, whereas values close to -1 and 1 denote a high correlation, negative or positive respectively.

As expected, the number of patents published and the number of patents granted are strongly correlated (0.89) with each other, as they are metrics closely related in the patenting process and both indicate companies' innovation output. Therefore, they are separated into two models as explained in the Methodology section. The published patent propensity and granted patent propensity variables, with a Pearson coefficient of 0.87, follow the same reasoning. The highest value is 0.99 and is the coefficient between net income and EBIT, which is a very strong correlation that naturally arises since both represent the financial health of the company and EBIT is a precursor to the net income figure. Not surprisingly there is a high positive correlation between variables related to firms' size, capacity, and performance as larger companies can obtain great benefits from their scale and resource availability.

Figure 2: Correlation matrix of variables



The high positive correlation (0.68) between R&D spendings and number of employees suggests that, firms with a higher number of workers tend to spend more on innovation activities, possibly because they are able to allocate more resources towards innovation.

5.3 Regression Model

The results of the regression model are reported in Table 4. The first column displays the estimation taking into account solely the explanatory variables, while in the second column all the control variables described in model 4.1 are added. Although Model 1 has a moderate adjusted R-squared value of 0.3392, Model 2 shows a strong R-squared value (0.5843), meaning that its variables explain about 58.61% of the variability in Tobin's Q, indicating a solid explanatory power.

Table 4: Results of the Regression Model

	Dependent variable:	
	Tobin's Q	
	Model 1	Model 2
R&D Intensity	0.10070*** (0.01116)	0.11670*** (0.00930)
Granted Patents	−0.00008*** (0.00001)	−0.00005*** (0.00001)
Total Assets		−0.29150*** (0.01454)
Total Intangible Assets		0.00277 (0.00158)
Total Sales		0.14450*** (0.01549)
Number of Employees		0.00000*** (0.00000)
Firm Age		0.02110** (0.00818)
Net Income		0.00000*** (0.00000)
Year Dummies	YES	YES
Sector Dummies	YES	YES
Constant	0.56660*** (0.04286)	2.98000*** (0.13190)
N. of Observations	1,248	1,248
N. of firms	208	208
Adj. R-squared	0.3392	0.5843

Note: Standard errors are given in parentheses. Tobin's Q, R&D Intensity, Total Assets, Total Intangible Assets, Sales, and Firm Age variables are log-transformed. Asterisks indicate significance levels: *p<0.05; **p<0.01; ***p<0.001

As expected, R&D intensity shows a positive and highly significant correlation (0.11670) with Tobin's Q. This means that companies that reinvest a higher percentage of their revenues in R&D activities are more likely to obtain a better performance, which confirms Hypothesis 1. This suggests that the market rewards companies that greatly invest in innovation activities. As previously stated, it is likely that investors perceive firms with great R&D intensity to have higher chances of maintaining long-term profitability since through innovation activities new products and technological advancements, which are fundamental to obtaining a sustainable competitive advantage, are created. However, this log-log transformation denotes diminishing marginal returns, meaning that, while initially great R&D intensity may significantly increase Tobin's Q values, this boost is likely to decrease with high R&D intensity values, which could be explained by the incrementally increasing costs and complexity of R&D investments. Therefore, investing in innovation activities is critical to enhancing companies' performance, but the R&D strategy should be balanced with firms' revenues and investments in other sources of competitive advantage.

Surprisingly, the analysis shows a statistically significant correlation with a negative coefficient between the number of granted patents and Tobin's Q, indicating an inverse relationship. This result suggests that, as opposed to what expected, the number of granted patents is associated with a decrease in Tobin's Q. Thus, Hypothesis 2 is rejected. There are different possible explanations for this result. First, since managing large patent portfolios can be very expensive for a firm, due to legal fees, maintenance, and administrative costs, it could be possible that if a patent does not generate substantial revenues, its costs might outweigh its benefits, decreasing the company's profitability and valuation. Then, it could mean that firms with a bigger amount of patents are overstretching their resources instead of focusing on innovation. Since the value of a patent can be very different from another, the market may perceive that companies that focus on patent quantity rather than quality are less innovative or are adopting particular defensive strategies, which may not have a positive impact on revenues, leading to a lower market value. Then, there is the possibility that companies adopt a defensive strategy by creating "patent thickets", large patent portfolios that have the scope of making it harder for competitors to innovate without violating an existing intellectual property right. In these environments, an increasing number of patents is likely to generate diminishing returns. Thus, such a case might lead to a negative perception by investors, which translates into a lower Tobin's Q value. Last, according to Teece's dynamic capabilities theory, patents alone might not be able to create significant value for a company, but it needs to have the necessary complementary assets, strategic alignment, and dynamic capabilities to fully acquire the value coming from patents. Thus, firms may lack these complementary abilities that would make them able to increase their profitability but instead negatively impact it.

Regarding control variables, there is a strong, negative, and statistically significant correlation (-0.29150) between total assets and firms' performance, meaning that bigger firms often have lower market valuations relative to their assets. It is possible that larger firms experience declining returns to scale or that the market perceives that bigger firms could achieve lower growth rates, leading to lower Tobin's Q values.

Although positive, with a p-value of 0.0805 the correlation between total intangible assets and Tobin's Q is not statistically significant in the analysis. As explained before with the number of patents granted, this could be due to the difficulty of evaluating intangible assets which could explain why their value is not reflected in the firm's market value.

Total sales, instead, show a strong, positive, and statistically significant correlation (0.14450) with the dependent variable. Unsurprisingly, as this indicator demonstrates the ability of a company to generate revenues and sustain operations, a higher figure is reflected by a higher evaluation since investors are likely to expect long-term profitability.

The number of employees, while significant, displays no correlation with firms' performance. This could be because, especially because of associated costs, a larger workforce does not always translate into higher profitability, as firms might not efficiently use their human resources. Moreover, in modern economies automation has taken over, making it unnecessary to have a large number of workers to reach a high profitability.

Firms' age has a positive coefficient of correlation of 0.02110, meaning that older companies are more valued by the market, possibly because their already established reputation, experience, accumulated customer loyalty, and stability are highly valued by investors.

Unexpectedly, according to the model, net income is not related with Tobin's Q. A possible explanation is that net income is an indicator of short-term profitability, which might be not what investors look at when assessing firms' potential, or that net income is not an accurate indicator for companies at their initial stages.

Robustness Test

Table 5: Robustness Tests Models

	Dependent variable:		
	Tobin's Q		
	Model 1	Model 2	Model 3
Published Patents	−0.00001		
	(0.00001)		
Granted Patents Propensity		−0.28400	
		(0.15180)	
Published Patents Propensity			−0.28380***
			(0.08004)
Total Assets	−0.26420***	−0.26950***	−0.27420***
	(0.01517)	(0.01504)	(0.01507)
Total Intangible Assets	0.00297	0.00308	0.00355*
	(0.00168)	(0.00168)	(0.00168)
Total Sales	0.10150***	0.10440***	0.10920***
	(0.01606)	(0.01615)	(0.01615)
Number of Employees	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
Firm Age	0.00232	0.00211	0.00245
	(0.00855)	(0.00851)	(0.00847)
Net Income	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
Year Dummies	YES	YES	YES
Sector Dummies	YES	YES	YES
Constant	2.96600***	1.70500*	1.71800***
	(0.14020)	(0.72000)	(0.39270)
N. of Observations	1,248	1,248	1,248
N. of firms	208	208	208
Adj. R-squared	0.53	0.5306	0.534

Note: Standard errors are given in parentheses. Tobin's Q, Granted Patents Propensity, Published Patents Propensity, Total Assets, Total Intangible Assets, Sales, and Firm Age variables are log-transformed. Asterisks indicate significance levels: *p<0.05; **p<0.01; ***p<0.001

To ensure the robustness of results, three additional analyses are conducted. In each of them, a single different independent variable is adopted, while Tobin's Q is always maintained as the dependent variable. All the control variables described in the Methodology chapter are included. In Model 1, the number of published patents is used as the explanatory variable. The number of published patents represents the number of patents of a firm that have been made publicly available through patent offices or databases in a given year. A high value is an indicator of ongoing R&D activities, which is likely to improve the firm's market perception and reputation for innovation, potentially attracting new investors and partners. This indicator is different from the number of granted patents since the two variables reflect different phases of the patenting process and could have a different impact due to differences in timing, market perception, and breadth of innovation captured. In Model 2, Granted Patents Propensity is used as the independent variable. This indicator is obtained by dividing the number of patents granted by R&D spending and indicates the effectiveness of the patent strategy and output. Higher values indicate that the firm is able to generate a significant amount of legally protected and commercially viable patents, which can influence the firm's value. Last, Model 3 uses Published Patents Propensity, calculated by dividing the number of patents published by R&D spending, as the explanatory variable. This ratio shows how efficiently a firm turns its R&D expenditure into patentable ideas and a larger value can reflect a more efficient innovation process.

Table 5 displays the results of the robustness tests. Both in Model 1 and Model 2, the coefficients are negative but statistically insignificant, meaning that the explanatory variables do not significantly impact Tobin's Q. However, Model 3 provides significant results. Indeed, Published Patents Propensity has a significant negative correlation (-0.28380) with Tobin's Q. These findings are consistent with the results obtained in the previous analysis that used the number of granted patents as independent variable, indicating that higher patent activity might reduce firm value. As previously explained, this may reflect inefficiencies in R&D activities, a focus on patent quantity rather than quality, or the adoption of defensive strategies.

Conclusions

This research aimed to better clarify the relationship between technological innovation and financial performance in companies by examining their R&D investments and patent activities. The analysis focused on companies included in the S&P 500 index and a dataset with their financial information over 5 years was constructed. The main innovation indicators implemented were R&D intensity and the number of patents granted, with Tobin's Q as the dependent variable to measure financial performance.

The key findings of the analysis indicate a positive correlation between R&D intensity and Tobin's Q. This result denotes that firms that allocate a higher percentage of their revenues on R&D are more likely to achieve higher profitability, which is consistent with existing literature. However, the results also show an unexpected negative relationship between the number of patents granted and Tobin's Q.

These findings are further confirmed with the robustness test, where also the Published Patent Propensity shows a negative correlation. Such results suggest that having a large number of patents does not necessarily translate into higher future profitability, but instead is likely to negatively impact firm value. Great costs associated with managing large patent portfolios, overlooking patent quality for quantity, and amassing patents for strategy purposes are possible causes of this negative relationship.

Despite the valuable findings, the study still has some limitations. The sample includes only large US companies with large resources, so these results may not apply to smaller firms or companies in other countries. In addition, there is a limited availability of firms' data on their R&D and innovation activities, which can sometimes be inaccurate or difficult to evaluate. Future research could address these limitations by enlarging the sample, if more precise data become available, and by using complementary data to qualitatively assess patents, for example concerning their technological significance and commercial viability. In this way, it might be possible to clarify which factors are most important for patents to have a positive effect on firm value and which ones have a negative impact.

In conclusion, this analysis demonstrated the substantial role of R&D investments in company performance and that obtaining a large number of granted patents alone does not positively impact firms' profitability, but rather affects it negatively. To achieve long-term sustainable success, companies should carefully plan their innovation strategies, as they significantly contribute to financial performance, but most importantly their patenting strategies, as they are likely to have negative effects on profitability. With further research, new studies could provide additional guidance on how to leverage innovation and patenting activities to contribute to company performance.

References

Adner, Ron. 2006. "Match Your Innovation Strategy To Your Innovation Ecosystem." *Harvard business review* 84 (May): 98–107, 148.

Alt, Philipp. 2018. "Does Innovation Pay Off in Terms of Firm Performance?-Evidence from the European Automotive Industry–." *MaRBLe* 1.

Amabile, Teresa, Mary Collins, Regina Conti, Elise Phillips, Martha Picariello, John Ruscio, and Dean Whitney. 2018. *Creativity in Context: Update to The Social Psychology of Creativity.* Westview Press., May. ISBN: 9780429501234. https://doi.org/10.4324/9780429501234.

Anderson, Eugene W, Claes Fornell, and Sanal K Mazvancheryl. 2004. "Customer satisfaction and shareholder value." *Journal of marketing* 68 (4): 172–185.

Autio, Erkko, and Llewellyn Thomas. 2014. "Innovation Ecosystems: Implications for Innovation Management," 204–228. Oxford University Press, January. ISBN: 978-0-19-969494-5.

Bardhan, Indranil, Viswanathan Krishnan, and Shu Lin. 2013. "Research note—business value of information technology: testing the interaction effect of IT and R&D on Tobin's Q." *Information Systems Research* 24 (4): 1147–1161.

Belderbos, Rene, Dries Faems, Bart Leten, and Bart Van Looy. 2010. "Technological activities and their impact on the financial performance of the firm: Exploitation and exploration within and between firms." *Journal of Product Innovation Management* 27 (6): 869–882.

Bigliardi, Barbara, Giovanna Ferraro, Serena Filippelli, and Francesco Galati. 2020. "The influence of open innovation on firm performance." *International Journal of Engineering Business Management* 12 (November): 1–14. https://doi.org/10.1177/1847979020969545.

Blind, Knut, Katrin Cremers, and Elisabeth Mueller. 2009. "The influence of strategic patenting on companies' patent portfolios." *Research policy* 38 (2): 428–436.

Blind, Knut, Jakob Edler, Rainer Frietsch, and Ulrich Schmoch. 2006. "Motives to patent: Empirical evidence from Germany." *Research policy* 35 (5): 655–672.

Brossard, Dominique. 2013. "New Media Landscapes and the Science Information Consumer." *Proceedings of the National Academy of Sciences of the United States of America* 110 (August). https://doi.org/10.1073/pnas.1212744110.

Brynjolfsson, Erik, and Andrew Mcafee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies.* Norton & Company.

Chauvin, Keith W, and Mark Hirschey. 1993. "Advertising, R&D expenditures and the market value of the firm." *Financial management,* 128–140.

Chen, Yu-Shan, and Ke-Chiun Chang. 2009. "Using neural network to analyze the influence of the patent performance upon the market value of the US pharmaceutical companies." *Scientometrics* 80:637–655.

Chen, Yu-Shan, and Chun-Yu Shih. 2011. "Re-examine the relationship between patents and Tobin's q." *Scientometrics* 89 (3): 781–794.

Chesbrough, Henry. 2003. *Open Innovation: The New Imperative for Creating and Profiting From Technology.* Vol. 21. Harvard Business Review Press, January. ISBN: 9781578518371.

Chin, Chen-Lung, Picheng Lee, Hsin-Yi Chi, and Asokan Anandarajan. 2006. "Patent citation, R&D spillover, and Tobin's Q: evidence from Taiwan semiconductor industry." *Review of Quantitative Finance and Accounting* 26:67–84.

Chintalapati, Srikrishna, and Shivendra Pandey. 2021. "Artificial intelligence in marketing: A systematic literature review." *International Journal of Market Research* 64 (July): 147078532110184. https://doi.org/10.1177/14707853211018428.

Chui, Michael, Eric Hazan, Roger Roberts, Alex Singla, Kate Smaje, Alex Sukharevsky, Lareina Yee, and Rodney Zemmel. 2023. *The economic potential of generative AI: The next productivity frontier.* July 15, 2024. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier.

Connolly, Robert A, and Mark Hirschey. 2005. "Firm size and the effect of R&D on Tobin's q." *R&d Management* 35 (2): 217–223.

Czarnitzki, Dirk, Bronwyn H Hall, Raffaele Oriani, et al. 2006. *The market valuation of knowledge assets in US and European firms.*

Dewar, Robert, and Jane Dutton. 1986. "The Adoption of Radical and Incremental Innovations: An Empirical Analysis." *Management Science* 32 (November): 1422–1433. https://doi.org/10.1287/mnsc.32.11.1422.

Enholm, Ida Merete, Emmanouil Papagiannidis, Patrick Mikalef, and John Krogstie. 2021. "Artificial Intelligence and Business Value: a Literature Review." *Information Systems Frontiers* 24 (August). https://doi.org/10.1007/s10796-021-10186-w.

Gassmann, Oliver, Ellen Enkel, and Henry Chesbrough. 2010. "The Future of Open Innovation." *R&D Management* 40 (June): 213–221. https://doi.org/10.1111/j.1467-9310.2010.00605.x.

Greco, Marco, Michele Grimaldi, and Livio Cricelli. 2016. "An analysis of the open innovation effect on firm performance." *European Management Journal* 34 (October): 501–516. https://doi.org/10.1016/j.emj.2016.02.008.

———. 2018. "Benefits and costs of open innovation: the BeCO framework." *Technology Analysis & Strategic Management* 31 (June): 1–14. https://doi.org/10.1080/09537325.2018.1484442.

Grigaitis, Julius. 2016. "Impact of Patenting on Profitability of Firms." Master's thesis, Erasmus School of Economics.

Henderson, Rebecca, and Kim Clark. 1990. "Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms." *Administrative science quarterly* 35 (March). https://doi.org/10.2307/2393549.

Hirschey, Mark, and Vernon J Richardson. 2004. "Are scientific indicators of patent quality useful to investors?" *Journal of Empirical Finance* 11 (1): 91–107.

Ivanov, Dmitry, Alexandre Dolgui, and Boris Sokolov. 2018. "The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics." *International Journal of Production Research* 57 (June): 1–18. https://doi.org/10.1080/00207543.2018.1488086.

Kaldor, Nicholas. 1966. "Marginal productivity and the macro-economic theories of distribution: comment on Samuelson and Modigliani." *The Review of Economic Studies* 33 (4): 309–319.

Kapetaniou, Chrystalla, Marios Samdanis, and Soo Hee Lee. 2018. "Innovation policies of Cyprus during the global economic crisis: Aligning financial institutions with National Innovation System." *Technological Forecasting and Social Change* 133:29–40. ISSN: 0040-1625. https://doi.org/https://doi.org/10.1016/j.techfore.2018.02.019. https://www.sciencedirect.com/science/article/pii/S0040162516308654.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2012. "Technological Innovation, Resource Allocation, and Growth." *SSRN Electronic Journal* (January). https://doi.org/10.2139/ssrn.2193068.

Kun-Hsing, Yu, Andrew Beam, and Isaac Kohane. 2018. "Artificial intelligence in healthcare." *Nature Biomedical Engineering* 2 (October). https://doi.org/10.1038/s41551-018-0305-z.

Malerba, Franco, and Pamela Adams. 2014. "183Sectoral Systems of Innovation." In *The Oxford Handbook of Innovation Management.* Oxford University Press, January. ISBN: 9780199694945. https://doi.org/10.1093/oxfordhb/9780199694945.013.030. eprint: https://academic.oup.com/book/0/chapter/215215099/chapter-ag-pdf/44586052/book_28362_section_215215099.ag.pdf. https://doi.org/10.1093/oxfordhb/9780199694945.013.030.

Maxwell, Elliot. 2006. “Open Standards, Open Source, and Open Innovation: Harnessing the Benefits of Openness.” *Innovations: Technology, Governance, Globalization* 1 (February): 119–176. https://doi.org/10.1162/itgg.2006.1.3.119.

Megna, Pamela, and Mark Klock. 1993. “The impact of intangible capital on Tobin’s q in the semiconductor industry.” *The American Economic Review* 83 (2): 265–269.

Moore, James. 1999. “Predators and Prey: A New Ecology of Competition.” *Harvard business review* 71 (May): 75–86.

Morandín-Ahuerma, Fabio. 2022. “?What is Artificial Intelligence?” *Int. J. Res. Publ. Rev* 3 (12): 1947–1951.

Nambisan, Satish, kalle lyytinen kalle, Ann Majchrzak, and Michael Song. 2017. “Digital Innovation Management: Reinventing Innovation Management Research in a Digital World.” *MIS Quarterly* 41 (January). https://doi.org/10.25300/MISQ/2017/41:1.03.

Neuhäusler, Peter, Rainer Frietsch, Torben Schubert, and Knut Blind. 2011. *Patents and the financial performance of firms-An analysis based on stock market data.* Technical report. Fraunhofer ISI Discussion Papers-Innovation Systems and Policy Analysis.

North, Douglass C. 1990. *Institutions, Institutional Change and Economic Performance.* Political Economy of Institutions and Decisions. Cambridge University Press.

Orsenigo, Luigi, Valerio Sterzi, et al. 2010. “Comparative study of the use of patents in different industries.” *Knowledge, Internationalization and Technology Studies (KITeS)* 33:1–31.

Patin, Jeanne-Claire, Matiur Rahman, and Michael E Roach. 2024. “EFFECTS OF R&D SPENDING ON TOBIN’SQ OF SELECTED TEN US IT COMPANIES.” *Finance & Accounting Research Journal* 6 (3): 395–407.

Pol, Eduardo, and Pgh Carroll. 2006. *An Introduction to Economics with Emphasis on Innovation.* Thomson. https://api.semanticscholar.org/CorpusID:151098553.

Porter, Michael E., and James E. Heppelmann. 2014. “How Smart, Connected Products Are Transforming Competition.” *Harvard Business Review* 92:18. https://api.semanticscholar.org/CorpusID:167014495.

Pramod, Kumar Naik, Narayanan Krishnan, and Padhi Puja. 2012. "R&D intensity and market valuation of firm: a study of R&D incurring manufacturing firms in India." *Indian Institute of Technology Bombay.*

PricewaterhouseCoopers. 2024. *2024 AI Business Predictions.* July 13, 2024. https://www.pwc.com/us/en/tech-effect/ai-analytics/ai-predictions.html.

Rahman, Md Musfiqur, and Md Shuvo Howlader. 2022. "The impact of research and development expenditure on firm performance and firm value: Evidence from a South Asian emerging economy." *Journal of Applied Accounting Research* 23 (4): 825–845.

Ransbotham, Sam, Philipp Gerbert, Martin Reeves, David Kiron, and Michael Spira. 2018. "Artificial Intelligence in Business Gets Real." *MITSloan Management Review* (September).

Rogers, Everett Mitchell. 1962. *Diffusion of Innovations.* Simon & Schuster. https://kb.osu.edu/server/api/core/bitstreams/56cc560a-46c7-5df8-81d8-340c1895b9f1/content.

Scherer, F. 2007. *Innovation and Growth: Schumpeterian Perspectives.* Vol. 52. MIT Press0, January. https://doi.org/10.2307/1059298.

Schumpeter, Joseph Alois. 1934. *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle.* https://api.semanticscholar.org/CorpusID:152358274.

———. 1939. *Business Cycles: A Theoretical Historical and Statistical Analysis of the Capitalist Process.* https://api.semanticscholar.org/CorpusID:260457371.

———. 1943. *Capitalism, Socialism and Democracy.* https://api.semanticscholar.org/CorpusID:155025632.

Segato, Alice, Aldo Marzullo, Francesco Calimeri, and Elena De Momi. 2020. "Artificial intelligence for brain diseases: A systematic review." *APL Bioengineering* 4 (December): 041503. https://doi.org/10.1063/5.0011697.

Sinek, Simon. 2017. *Creativity in Context: Update to The Social Psychology of Creativity.* Portfolio / Penguin. ISBN: 978-1-101-62303-9.

Singhal, Rajeev, Liang Fu, and Mohinder Parkash. 2016. "Tobin's q Ratio and Firm Performance." *International Research Journal of Applied Finance* VII (April). https://doi.org/10.0704/article-2.

Śledzik, Karol. 2013. "Schumpeter's View on Innovation and Entrepreneurship." *SSRN Electronic Journal* (April). https://doi.org/10.2139/ssrn.2257783.

Thornhill, Stewart. 2006. "Knowledge, innovation and firm performance in high- and low-technology regimes." *Journal of Business Venturing* 21 (September): 687–703. https://doi.org/10.1016/j.jbusvent.2005.06.001.

Tidd, Joe, and John Bessant. 2021. *Managing Innovation Integrating Technological, Market and Organizational Change.* Wiley, January. ISBN: 978-1-119-71330-2.

Tobin, James. 1969. "A general equilibrium approach to monetary theory." *Journal of money, credit and banking* 1 (1): 15–29.

Tomaev, Nenad, Julien Cornebise, Frank Hutter, S. Mohamed, Angela Picciariello, Bec Connelly, Danielle Belgrave, et al. 2020. "AI for social good: unlocking the opportunity for positive impact." *Nature Communications* 11. https://api.semanticscholar.org/CorpusID:218670798.

Trippe, Anthony J. 2022. "Knowledge management with patents: A systematic method for capturing and sharing unique technical information for Corporate guidance." *World Patent Information* 69:102110.

USPTO. 2024. *Applying for Patents.* June 29, 2024. https://www.uspto.gov/patents/basics/apply.

Valente, Thomas W. 1996. "Social network thresholds in the diffusion of innovations." *Social Networks* 18 (1): 69–89. ISSN: 0378-8733. https://doi.org/https://doi.org/10.1016/0378-8733(95)00256-1. https://www.sciencedirect.com/science/article/pii/0378873395002561.

Valkokari, Katri. 2015. "Business, Innovation, and Knowledge Ecosystems: How They Differ and How to Survive and Thrive within Them." *Technology Innovation Management Review* 5 (August): 17–24. https://doi.org/10.22215/timreview/919.

Wejnert, Barbara. 2002. “Integrating Models of Diffusion of Innovations: A Conceptual Framework.” *Annual Review of Sociology - ANNU REV SOCIOL* 28 (August): 297–326. https://doi.org/10.1146/annurev.soc.28.110601.141051.

WIPO. 2024. *Patents.* June 27, 2024. https://www.wipo.int/web/patents.

Appendix

Table 6: Sample Distribution by Sector

3-digit SIC code	Sector	No. of firms	No. of obs.
102	Copper ores mining	1	6
104	Gold and silver ores mining	1	6
131	Crude petroleum and natural gas mining	4	24
138	Oil and gas field services	2	12
162	Heavy construction, except highway	1	6
201	Meat product manufacturing	2	12
203	Preserved fruit and vegetables manufacturing	4	24
204	Grain mill products manufacturing	1	6
205	Bakery products manufacturing	1	6
206	Sugar and confectionery products manufacturing	1	6
208	Beverages manufacturing	2	12
209	Miscellaneous food and kindred products manufacturing	3	18
211	Cigarettes manufacturing	2	12
242	Sawmills and planing mills manufacturing	1	6
267	Miscellaneous converted paper products manufacturing	1	6
281	Industrial inorganic chemicals manufacturing	1	6
282	Plastics materials and synthetics manufacturing	2	12
283	Drugs manufacturing	16	96
284	Soap, cleaners and toilet goods manufacturing	5	30
285	Paints and allied product manufacturing	2	12
286	Industrial organic chemicals manufacturing	2	12
287	Agricultural chemical manufacturing	1	6
291	Petroleum refining manufacturing	6	36
302	Rubber and plastics footwear manufacturing	1	6
335	Nonferrous rolling and drawing manufacturing	1	6
341	Metal cans and shipping containers manufacturing	1	6
348	Ordnance and accessories manufacturing, NEC	1	6
349	Miscellaneous fabricated metal products manufacturing	2	12
351	Engines and turbines manufacturing	1	6
352	Farm and garden machinery manufacturing	1	6
353	Construction and related machinery manufacturing	2	12
355	Special industry machinery manufacturing	2	12
356	General industrial machinery manufacturing	3	18
357	Computer and office equipment manufacturing	8	48
358	Refrigeration and service machinery manufacturing	1	6

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Table 6: Sample Distribution by Sector (continued)

3-digit SIC code	Sector	No. of firms	No. of obs.
362	Electrical industrial apparatus manufacturing	3	18
364	Electric lighting and wiring equipment manufacturing	1	6
366	Communication equipment manufacturing	4	24
367	Electronic components and accessories manufacturing	18	108
369	Miscellaneous electrical equipment and supplies manufacturing	1	6
371	Motor vehicles and equipment manufacturing	7	42
372	Aircraft and parts manufacturing	8	48
374	Railroad equipment manufacturing	1	6
381	Search and navigation equipment manufacturing	1	6
382	Measuring and controlling devices manufacturing	14	84
384	Medical instruments and supplies manufacturing	15	90
385	Ophthalmic goods manufacturing	1	6
394	Toys and sporting goods manufacturing	1	6
448	Water transportation of passengers	3	18
472	Passenger transportation arrangement	1	6
481	Telephone communications	1	6
492	Gas production and distribution	1	6
506	Electrical goods wholesale trade	1	6
512	Drugs, proprietaries and sundries wholesale trade	1	6
596	Nonstore retailers	1	6
599	Retail stores, NEC	1	6
701	Hotels and motels services	1	6
737	Computer and data processing services	26	156
738	Miscellaneous business services	7	42
784	Video tape rental	1	6
873	Research and testing services	2	12

Table 7: Additional Models

Description: This table provides the results of four additional models, where the two independent variables, R&D intensity and number of granted patents, are analyzed independently. Model 1 uses R&D intensity as the only explanatory variable and with no control variables, while model 2 takes them into account. Model 3 adopts the number of granted patents as the explanatory variable without including control variables, that however are added in Model 4.

	Dependent variable:			
	Tobin's Q			
	Model 1	Model 2	Model 3	Model 4
R&D Intensity	$0.0.08725^{***}$	0.10890^{***}		
	(0.01131)	(0.00923)		
Granted Patents			-0.00007	-0.00003^{*}
			(0.00001)	(0.00001)
Total Assets		-0.30100^{***}		-0.26100^{***}
		(0.01452)		(0.01522)
Total Intangible Assets		0.00259		0.00302
		(0.00159)		(0.00168)
Total Sales		0.14230^{***}		0.10040^{***}
		(0.01562)		(0.01603)
Number of Employees		0.00000^{**}		0.00000^{***}
		(0.00000)		(0.00000)
Firm Age		0.01530		0.00355
		(0.00815)		(0.00856)
Net Income		0.00000^{***}		0.00000^{***}
		(0.00000)		(0.00000)
Year Dummies	YES	YES	YES	YES
Sector Dummies	YES	YES	YES	YES
Constant	0.51865^{***}	3.17600^{***}	0.29220^{***}	2.92200^{***}
	(0.04348)	(0.12610)	(0.03114)	(0.013990)
N. of Observations	1,248	1,248	1,248	1,248
N. of firms	208	208	208	208
Adj. R-squared	0.3061	0.5772	0.2962	0.5314

Note: Standard errors are given in parentheses. Tobin's Q, R&D Intensity, Total Assets, Total Intangible Assets, Sales, and Firm Age variables are log-transformed. Asterisks indicate significance levels: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$