LUND UNIVERSITY

SCHOOL OF ECONOMICS AND MANAGEMENT

R&D Volatility and Market Value in the Pharmaceutical Industry.

An empirical study on moderating effects of size and R&D intensity in the U.S. market

Degree Project (M.Sc.)

BUSN79 – Accounting and Finance

Lund University

School of Economics and Management

Marco Labasin and Axel Nobréus

ABSTRACT

Seminar date: 31-May-2023

Course: BUSN79 - Degree Project in Accounting and Finance

Authors: Marco Labasin, Axel Nobréus

Advisor: Reda Moursli

Key Words: Pharmaceutical, R&D Volatility, Firm Market Value, Firm Size, R&D Intensity

Purpose: We examine the relationship between R&D volatility and firm market value in the U.S. pharmaceutical industry during the period of 2012-2022.

Methodology: Multiple linear OLS regression of R&D volatility on Tobin's Q, considering the moderating effects of size and R&D intensity.

Theoretical Perspectives: R&D investments impact on information asymmetry; Signaling Theory; Agency Theory

Empirical Foundation: Data has been retrieved from S&P CapitalIQ, with a sample consisting of 870 firms exchanged in the U.S., providing 4346 firm-year observations in the period 2012-2022.

Conclusions: The positive outlook of proactive management considered in the analysis leads to a more favorable view of R&D expenditure volatility, which is supposed to discourage managerial myopic behavior. Therefore, the stakeholders that we addressed, should view R&D expenditure volatility favorably given its positive relationship with firm market value. However, size is a factor that must be taken into consideration, since larger firms have different stakeholders and their interests are more heterogeneous.

ACKNOWLEDGEMENTS

We would like to thank our supervisor, Reda Moursli, for his guidance and support. He has provided us with valuable insights and guidance along the process. We would also like to extend our gratitude to friends and family who have supported us throughout our studies.

Table of Contents

1. INTRODUCTION

1.1 R&D IN PHARMACEUTICALS AND DRUG DEVELOPMENT

Research is a fundamental aspect of the pharmaceutical industry driving medical progress and the development of new drugs and active ingredients as evidenced by a Research and Development (R&D) spending as a share of net revenues of 25% in 2017 compared to the average of 2% to 3% in all industries (Congressional Budget Office, 2021). The R&D process in the industry is lengthy and costly with proportionate sunk costs associated with projects, in fact, the expected development cost of a new drug incorporating failed projects, range from 1$ billion to 2$ billion (Congressional Budget Office, 2021). Companies in the pharmaceutical, life sciences, and biotechnology sectors allocate a significant portion of their budgets each year to R&D costs. The appraised cost of R&D in the industry amounted to $83 billion in 2019 in the U.S., which represents an amount 10 times greater than the average yearly R&D spending of the industry in the 1980s (Congressional Budget Office, 2021). These capital efforts have also led to an increase in research and development outcomes. Between 2010 and 2019, the number of new drugs approved by the Food and Drug Administration (FDA) for the U.S. market has been 60% higher than the previous decade (Congressional Budget Office, 2021). Even though both R&D expenditures and drug approvals have experienced an increase in the past five years, the relationship between them is not direct and linear, considering the different amounts of investments that firms need to dedicate to R&D projects (Congressional Budget Office, 2021).

The average time for new medicine to reach patients is 10 years in the U.S. (Biopharmaceutical Research & Development: The Process Behind New Medicines, 2015). The combination of the extensive time it takes for medicines to reach patients and the low probabilities of 12% success rate (Congressional Budget Office, 2021) as measured in the approval of new medicines may raise questions about what an appropriate level of R&D expense should be. Yet, the R&D intensity of publicly traded U.S. pharmaceutical firms has on average increased by 19 percent in the last two decades (Congressional Budget Office, 2021). This could signal that the view of expected returns in R&D investments has changed for the better, and hence the market reacts positively towards increased R&D expenditure.

Each drug and product must undergo a long and meticulous process to get approved by the different agencies responsible for medical product commercialization around the world. In the

USA, the responsible agency is the FDA, which requires a multiple-step process to assure the necessary safety and quality of the product. The main steps consist of pre-clinical experiments on animals, followed by clinical research involving 3 different phases of sampling on human subjects where the last is a large-scale study, and finally the review of the phases by the FDA with potential approval of the drug recipe (Center for Drug Evaluation and Research, 2019). These steps take years to complete, and, according to researchers, the share of drugs that fulfill all the steps is limited. Wong et al. (2018) found that only 13.8% of the drug development programs are approved, and their findings are in line with the 12% approval rate reported by Congressional Budget Office (2021).

A peculiarity in the distribution of drugs in the late stages of the approval process (phase III) is that more than 70% of them are being developed by small firms, suggesting that companies with limited resources are still able to impact the market (Congressional Budget Office, 2021). The same small firms also represent a desirable target for potential buyouts. This trend is confirmed by the fact that the pharmaceutical mergers and acquisition market is becoming more active since it represents an efficient way for big firms to acquire R&D in progress. In fact, one in every five drugs in development has been acquired by another pharmaceutical company (Congressional Budget Office, 2021). This implies that a correct firm market value is increasingly fundamental in this environment. Therefore, the historical trend of R&D expenses is a relevant argument for market valuation, particularly when the amount of money spent in medicine each year has experienced a solid and constant rise in the last 20 years, more than doubling its size in the increase from $195 billion to $574 billion in the U.S. market (U.S. total medicine spending 2002-2021, 2022).

The decision to pursue certain R&D for new drugs depends on a list of factors. Pharmaceutical companies consider the projected revenue over the lifetime of the drug, the R&D costs associated with it, and lastly, any policies that influence the demand or supply for it (Congressional Budget Office, 2021). The government's policies strongly influence the spending for R&D in different ways: increasing demand for prescription drugs by giving economic incentives for the patients, increasing the supply of the drugs by providing subsidies for the research processes, and finally influencing the whole market by a coordinated action of incentives and subsidies (Congressional Budget Office, 2021). All these factors give pharmaceutical companies reasons to forecast more optimistic scenarios.

We would expect to observe that when anticipated revenues for drugs are higher, the predicted response is to increase R&D spending. This would imply higher R&D volatility, which, according to Mudambi and Swift (2011), indicates proactive R&D management. Accordingly, proactive management demonstrates ambidextrous capabilities for firms and helps them achieve sustained growth. The market values sustained growth and may consequently value R&D volatility.

1.2 MOTIVATION

The literature on R&D corporate financial studies developed from focusing on R&D intensity to studying the volatility of the expenditures and the heterogenous causes for such changes (Mudambi and Swift, 2011; Mudambi and Swift, 2014; Wang et al., 2016; Hai et al., 2019; Xiang et al., 2020; Mironiuc et al., 2022). Since the literature findings were divisive and provided mixed evidence, Kang et al. (2017) completed a thorough review of past literature approaches, considering their theoretical perspectives and the empirical evidence resulting from the different works. Based on the idea that heterogeneity across firms' R&D investment policies is at the root of inconsistency in previous research (Kang et al., 2017), we decided to start our approach by considering one specific industry, characterized by a heavily regulated R&D process, like pharmaceutical, biotechnologies and life sciences.

A similar study from Mironiuc et al. carried out in 2022, analyzes pharmaceutical firms traded in Europe in the period 2014-2019. Following their suggestion on improving their results, we extend the time period and take into consideration additional perspectives. Therefore, since we aim to fill the gap in the literature, we analyze pharmaceutical firms in the U.S., following the approach of the frontier of research on R&D expenditure, by studying the volatility of them and giving additional evidence for potential moderating effects.

Our research follows these questions throughout the paper: "To what extent does R&D volatility have a significant effect on market value in the pharmaceutical industry? Do factors, such as size and R&D intensity, have a moderating effect on the aforementioned relationship?".

1.3 MAIN FINDINGS AND CONTRIBUTION

Exploring the research question led us to investigate the impact that R&D volatility has on market valuation for U.S.-listed pharmaceutical firms using a multiple linear regression model. The results obtained provide evidence towards a positive significant effect of R&D volatility on the dependent variable Tobin's Q, and support the hypothesis that size moderates this

relationship with negative impact on market evaluation of R&D volatility. Findings on the moderating effect of R&D intensity do not provide significant results, suggesting that the independence among variables do not allow an additional explanation from the interaction term.

Our findings contribute to the field of research by addressing a divisive literature perspective on the R&D volatility effect by focusing on the pharmaceutical industry. The results and their economic interpretation are expected to provide more context and empirical research to stakeholders. Among others, investors, professional analysts and industry decision-makers are the main targets of our findings, since they are responsible for the market valuation and firms' policy making decisions. The positive outlook of proactive management considered in the analysis leads to a more favorable view of R&D expenditure volatility, which is supposed to discourage managerial myopic behavior. Therefore as a general stance, the stakeholders that we addressed, should view R&D expenditure volatility favorably given its positive relationship with firm market value. However, size is a factor that must be taken into consideration, since larger firms have different stakeholders and their interests are more heterogeneous.

1.4 OUTLINE OF THE PAPER

The paper provides an extensive explanation of the current state of the literature and uses literature gaps and prompts to formulate the hypothesis to be tested empirically. After having stated the hypothesis and presented their contribution, the sample is presented, and it includes firms traded in the U.S. between 2012 and 2022. The variables employed in the quantitative analysis are: Tobin's Q as the dependent, R&D volatility, size and R&D intensity as the main explanatory variables, and a series of widespread control variables. A thorough explanation of the methodology used will provide sufficient understanding of the empirical process, which consists of a multiple linear regression using OLS estimators and employing fixed effects together with standard errors clustered by subindustry in the preferred model. Results from the three hypotheses are consequently presented and analyzed in light of the literature, considering their reliability, giving insights and empirical evidence for researchers and industry professionals. Alongside results, robustness checks are carried out to increase reliability of the previous results. Finally, in the conclusion we address the research's contribution and we propose future research improvements.

2. LITERATURE REVIEW

2.1 THEORETICAL FRAMEWORK

2.1.1 R&D investments impact on information asymmetry

Akerlof (1970)'s study on quality uncertainty present in marketplaces contributed to the commonly referred concept of information asymmetry, where one party holds superior information as opposed to the other party. Within the pharmaceutical industry, R&D projects can be complex for external observers to comprehend, making it difficult to assess the risks and returns associated with those projects. Consequently, information asymmetry becomes significant in this industry given the attributes in R&D investments. One such attribute is that R&D investments are unique and therefore challenging to compare (Aboody and Lev (2000). This attribute makes it difficult to derive information on one firm's value based on the observation of R&D projects of another firm within the same industry. For instance, an FDA drug approval for Johnson & Johnson provides little to no information on a current drug development program by AbbVie. Consequently, the unique attributes of R&D investments in the pharmaceutical industry contributes towards information asymmetry. In fact, Aboody and Lev (2000) conclude that R&D activities enhance information asymmetry.

Another attribute of R&D investments that differentiates it from tangible investments is their accounting treatment. The accounting rules of R&D further aggravates information asymmetry since investors are not periodically informed regarding the value of R&D projects as they are when it comes to financial or tangible assets (Aboody and Lev, 2000). It may therefore be to no surprise that Aboody and Lev (2000) found that insider trading gains from R&D active firms were substantially larger than those firms that do not conduct R&D, providing evidence of increased information asymmetry due to R&D investments. Additionally, as opposed to markets trading financial or tangible assets, the lack of organized markets in R&D (Aboody and Lev, 2000) further contributes to information asymmetry.

2.1.2 Signaling Theory

Spence (1973) initially introduced the signaling theory and proposed signaling as a tool to minimize information asymmetry in the labor market where high-quality job candidates engage in behavior that distinguish themselves from low-quality candidates. The underlying responsibility of the theory is the reduction of information asymmetry between two parties (Spence, 2002). In the case of our study, the two parties are namely the investors and firms.

The effectiveness of a signal depends on the cost of the sender to communicate it followed by the observability, and lastly the verifiability of it (Hottenrott et al., 2015).

A common view amongst economists entails that capital market imperfections discourage investments in R&D due to the information gap between firm and investor (Hottenrott et al., (2015). Consequently, the information gap leads to a funding gap as the cost of external capital increases with more uncertainty around the success rates of new R&D projects. Therefore, Hottenrott et al., 2015 mentions the importance for R&D intensive firms to signal the quality of their activities and reduce information asymmetry and ultimately minimize the financial constraints caused by the funding gap. One way to signal the quality of the firm is the use of patents as obtaining them is costly and they can be both observed and verified by external parties (Long, 2002). Drug patents can compensate for the incurred costs in the R&D stage, and hence patents derived from R&D projects can be considered evidence of a successful outcome. These patents can vary from the production process to the chemical compound and the current patent term for an invention is 20 years in the US (FDA, 2020; Hickey, 2020). Long (2002) claimed that patents are useful in mitigating information asymmetry as they provide credible information to external parties.

The level of volatility in R&D expenditure is an additional mechanism that signals the firm value to investors. In fact, Jeny and Moldovan (2020) state that investors become more reluctant when observing high volatility of R&D expenditure as it subsequently leads to an increased investment risk. This reaction from investors implies that the level of volatility in R&D expenditure is a signal for risk averse investors to allocate their capital elsewhere. It seems that the signal to avert firms with high volatility in R&D expenditure derives from the uncertain reasons that cause the volatility. For instance, when there is an explanation behind the R&D expenditure volatility, it becomes positively related to the share returns (Aboody and Lev, 2000). However, according to Xiang (2020), persistence in R&D investments means avoiding adjustment costs, positioning the firm at a sustainable competitive advantage. If so, this would signal to investors that high R&D volatility is something negative.

2.1.3 Agency Theory

Building on the unique attributes of R&D projects and their contribution towards information asymmetry between the investor and firm, we open the argument that this could incentivise agency problems. Agency problems were introduced by Jensen and Meckling in 1976 describing that they occur when the self interests of the agent dominate the interests of the

principal (Eisenhardt, 1989). Management is commonly referred to as the agent and shareholders as the principal. One such case where management acts in self interest is when over or underinvesting in R&D. The high failure rates in R&D projects is an attribute that demotivates managers from investing in them as it can hurt short-term earnings and subsequently their reputation or bonus (Myers, 1977). On the contrary, it is common for risk-averse managers to overinvest in dying R&D projects as opposed to paying dividends or carry out share buybacks (Jensen, 1993). Under Generally Accepted Accounting Principles (GAAP), firms must expense their R&D in the same year as the cost incurred. As a result, optimistic managers may underinvest in R&D projects to smooth earnings. Further, they can also end up overinvesting in failing R&D projects with negative net present value to prevent sunk costs (Jensen 1993). R&D projects therefore provide a ground for myopic managerial behavior, and engaging in such can lead to over and underinvestments in R&D. As a result, management's actions interfere with the interests of shareholders, leading to an agency problem.

2.2. EMPIRICAL LITERATURE

The purpose of the literature review is to provide a comprehensive overview of existing research on the topic. It should carve a path for an understanding of the role that R&D expenditure has on market value for pharmaceutical, biotechnology, and life science firms.

2.2.1 Myopic behavior

The cause of the volatility in R&D expenditures across organizations can be debated. Duppati et al. (2017) argue that the myopic behavior of managers is one reason by investigating the relationship between board characteristics, firm performance, and R&D expenditure using ROA and Tobin's Q as proxies for financial performance with a sample of firms from Ireland and Spain between 2005-2014. The myopic behavior of managers as a cause of R&D volatility is further supported by Cheng (2004), who studied R&D expenditure in association with CEO compensation in R&D intensive industries between 1984-1997 based on 160 Forbes 500 firms, raising awareness of agency problems. However, companies with complex R&D investments are punished for managerial myopia (Tong and Zhang, 2014a). This suggests that although managerial myopia can be a cause of R&D volatility, it may not be a sufficient reason under the assumption that capital markets are efficient and should act as a stabilizer through punishment of myopic activities, and hence preventing such behavior (Tong and Zhang, 2014a). This leads to more control from the board of directors on R&D projects (Tong and

Zhang, 2014b) and expects fewer firms to pursue such activities, suggesting that R&D volatility is not a result of myopic behavior.

2.2.2 R&D expenditure volatility and firm market valuation

While on the topic of R&D management, Mudambi and Swift (2011) set the stage by proposing that proactive R&D management will help firms achieve sustained growth. They studied the relationship between R&D expenditure and volatility with firm growth on almost 11,000 publicly traded U.S. firms between 1997-2006. In doing so, they suggest that R&D expenditure volatility indicates proactive R&D management. Mudambi and Swift (2011) regard R&D expenditure volatility as evidence of firms shifting between exploitative and explorative activities. The R&D activities can be categorized into exploiting extant competencies and explorative efforts to discover new innovations (Mudambi and Swift, 2014). According to Mudambi and Swift (2011), "ambidextrous" firms, defining their ability to simultaneously focus on both, are considered best performing firms. As a result, this performance should be reflected in the market valuation of such firms. The main criticism with the ambidextrous concept is that exploitative and explorative activities cannot co-exist as the two are incompatible and firms must decide which path to follow. Mudambi and Swift (2011) included firms with sales greater than $50 million in all industries in their study, and it is therefore relevant to investigate if the same holds true in the pharmaceutical, biotechnology, and life science firms which may not experience any sales.

Mudambi and Swift (2011) concluded that R&D expenditure volatility positively relates to firm growth, and that this volatility represents a shift from exploitative to explorative R&D activities. In other words, a shift from exploitative to explorative activities disrupt the R&D spending. Further, particularly in the pharmaceutical industry, greater R&D expenditure is required for early-stage product development as opposed to late-stage work, advocating for exploratory R&D to be more costly (Mudambi and Swift, 2014). Given that exploratory activities are deemed more costly, a shift from exploitative activities should increase R&D expenditure and vice versa for a shift from explorative activities (Mudambi and Swift, 2014). Additionally, exploratory R&D can be portrayed as uncertain and when Mudambi and Swift (2014) studied 3,089 publicly traded U.S. manufacturing firms in 2002-2006, they suggest that firms undertake this when faced with a lack of alternatives. Also, Pennetier et al., (2018) observed volatility in R&D expenditure for firms in uncertain environments as new research opportunities are both regularly revealed and discontinued in such settings.

2.2.3 Accounting treatment of R&D

An observation made in R&D spending and its relation to earnings is further noteworthy. It was found that R&D spending was more prone to be reduced as the CEO was closer to retirement, or if the firm is probable to miss an earnings objective (Mudambi and Swift, 2014). On the other spectrum, high cash flow volatility firms often forego or delay R&D investments (Mudambi and Swift, 2014). Given these observations, it is interesting to examine how the market values R&D investments considering the argument of Mudambi and Swift (2014) that firms that move between exploitative and explorative R&D generate greater firm value.

Although many variables and factors impact market value of firms, the accounting treatment can be considered to have direct influence on its valuation. Wang et al. (2016) observed that capitalizing or expensing the R&D investment stipulated varied implications on firm value. The trend identified was that firms deciding to capitalize their investment achieved a higher market value whereas firms expensing their investment experienced a higher accounting performance. This suggests that the R&D policy choice can further impact the market valuation of a firm.

2.2.4 Technological capabilities and firm size

It is important to bear in mind that firm capability can influence the R&D strategy of certain firms. To some extent, firm capability may be dictated by the size of said firm given their available resources. Kang et al. (2017) explored a relationship between a firm's technological capability and volatility of R&D investments over time with data of 2,456 Korean firms between 2002-2009. In their study, they found that more capable firms could have both more persistent R&D investments given that they were more likely to continue to invest in R&D over time, but also more volatile R&D investments. Kang et al. (2017) argues that this is because they are more responsive to changes in the technological environment and thus adjust their R&D strategy in accordance. As size can affect such capabilities of firms, it should be a focus area in exploring the market reaction to R&D expenditure volatility. Xiang et al. (2020) studied the relationship between R&D volatility and return of 5,178 US listed firms between 1980 to 2018. A negative relationship was observed between R&D volatility and return, and this was moderated by firm size. Hence, for larger firms, the market reacts negatively towards disruptive R&D spending, whereas positively in small firms. Xiang et al. (2020) justifies this reaction in smaller firms by means of restricting technocrats from overinvesting in R&D, or in other words, a governance mechanism to control R&D spending.

2.2.5 Arguments for persistency or volatility in R&D investments

To better understand what drives the decision of persistency or volatility in R&D investments by firms, Kang et al., (2017) suggested examining firm specific technological capabilities as formerly mentioned. In light of Mudambi and Swift (2014) argument that high cash flow volatility firms often forego or delay R&D investments, it is important to create heterogeneity in studying firms R&D investments volatility or persistency to ultimately understand its effect on market valuation. Kang et al., (2017) created this heterogeneity with the introduction of technological capabilities, to better explain the asymmetric R&D investments. They examined the effect technological capabilities had on internal cash flows and found that choice of R&D policy (persistency or volatility) is not a mutually exclusive decision as it is dependent on the firm's capabilities.

Previous literature on R&D volatility has been divided in regard to persistency and volatility in R&D investments. Much of the past research has considered R&D investments from a static perspective whereas Kang et al., (2017) emphasizes the importance of viewing it from a dynamic one, given that current R&D investments are influenced by previous ones. Therefore, from a dynamic approach, we want to study the persistency and volatility of R&D investments to conclude the effect it has on market value. Brown and Petersen (2011) argued that persistent R&D investments recur in firms due to high adjustment and sunk costs associated with these investments. This means that, despite external environmental changes, firms are incentivized to keep their R&D investments consistent to minimize such costs. Volatile R&D investments on the other hand, as Kang et al., (2017) mentions, is dependent on the R&D investment source. For example, external financing is more costly and associated with higher risk due to information asymmetry, leading to more fluctuations in R&D investments.

The past literature has conflicting reasonings for firms attaining persistency or volatility in their R&D investments. Considering the high dependency of researchers as employees and the risk of losing talent towards competitors within R&D investments, Bernstein and Nadiri (1989) demonstrate that the marginal adjustment costs are higher for R&D investments than physical investments. High adjustment costs in such investments are reasons for persistency (Hall, 2002). Furthermore, the history of sunk costs in R&D investments is an additional cause for persistency (Máñez et al., 2009). On the other spectrum, Hall and Lerner (2009) argue that volatility in R&D investments are a result of the source of financing. Additionally, proactive

R&D management, as proposed by Mudambi and Swift (2011), provides a rationale towards volatility in R&D investments. While studying the relationship between R&D expenditure and volatility with firm growth, they posit that R&D expenditure volatility indicates proactive management, and regard it as evidence for firms shifting from exploitative towards explorative R&D. Moreover, Mudambi and Swift (2014) propose that firms making this shift generate greater firm value. This should therefore be reflected in the firm's market valuation.

The market reaction towards volatility in R&D varies according to existing literature. For instance, volatility in R&D expenditure may be positively viewed by the market for large firms operating in dynamic industries (Mironiuc et al., 2022; Demirel and Mazzucato, 2012). Conversely, a negative market reaction can be observed when managerial myopia is the cause for volatility in R&D expenditure (Tong and Zhang, 2014a). Consequently, in order to get a richer understanding of the links between the volatility of R&D expenditure and firm market valuation in our target industry, it is necessary to perform additional empirical research.

3. HYPOTHESES

The purpose of this study is to investigate the following hypotheses concerning firms in the pharmaceutical, biotechnology, and life science industry. Following the modern literature approach, our research takes into consideration R&D expenses in pharmaceutical, biotechnology and life sciences firms traded in the U.S., and aims at understanding the impact that changes in such expenses have on their market value. The doubts that the research aims at clarifying are related to different questions: To what extent is the volatility of R&D expenditures relevant for a firm's market valuation? To what extent are characteristics related to firm size or R&D intensity relevant when establishing the relationship between R&D volatility and market value?

3.1 R&D VOLATILITY AND FIRM VALUE

The effect that R&D expenditure volatility has on firm market value is a studied concept. Mironiuc et al (2022) investigated this relationship and found a weak negative effect on market value of the studied firms. However, the sample was based on European firms in a period from 2014 to 2019. Instead, by studying in the U.S. the pharmaceutical industry, which is also heavily R&D dependent, we expect to see a relevant relationship. As supported by Aboody and

Lev (2000), investments in R&D further enhance information asymmetry between investor and firm. In consideration of the increasing effect that R&D has on information asymmetry, we argue that R&D expenditure volatility will influence the market value of firms. Since R&D investments in the pharmaceutical industry can be difficult for external parties to observe, we assume that R&D expenditure volatility may influence the knowledge gap and impact market value as a result.

In order to give significance to the following hypothesis, the research selects as a starting point the general background that R&D expenditures are relevant in the market valuation of pharmaceutical firms. Since the market aims for efficiency by reducing information asymmetry with additional news or signals, we expect that the market observes the volatility in R&D expenditures as they indicate the state of the R&D in place. Therefore, we expect the market to consider this when evaluating a firm. The expectation is to find a significant effect, in line with the literature, and results that could clear the doubts surrounding the direction and magnitude of the effect. (Mudambi and Swift, 2011; Mudambi and Swift, 2014; Wang et al., 2016; Kang et al., 2017; Hai et al., 2019; Xiang et al., 2020; Mironiuc et al., 2022). The first hypothesis tackled is the starting point of the general research approach. We aim at studying the effect that R&D volatility has on the market valuation of publicly traded firms.

Hypothesis 1: R&D volatility has a significant effect on a firm's market valuation.

3.2 FIRM SIZE

Firm size is renowned for being taken into consideration in market evaluation and has a relevant effect on knowledge strategy and competitive success (Gopalakrishnan and Bierly, 2006). This may be because larger firms experience certain advantages including learning benefits associated with the affordability of failing but also having the convenience of enjoying economies of scale in their R&D investments (Cohen and Levinthal, 1990). As evidence of this, Cohen and Klepper (1992) showed that the returns associated with R&D investments were conditioned by firm size. However, there are also advantages that smaller firms experience such as having less impactful bureaucratic burdens (Walter, 2012). Arora et al., (2009) strengthens this point by providing evidence that small biotechnology firms are more innovative than large pharmaceutical firms. Therefore, the next step in our study involves considering a potential moderating effect of firm size in the relation between R&D volatility and market value, following Xiang et al. (2020). In fact, Xiang (2020) associates a positive

relationship between return and R&D volatility for smaller firms. This could be because it reduces overinvestment caused by agency issues. For instance, the size of the firm serves as a governance mechanism controlling the R&D spending. This way, a firm is less likely to experience agency issues when smaller. The effect is expected to be relevant, considering that size significantly modifies the market valuation, and therefore should modify the scope and scale at which R&D volatility is evaluated. Understanding this relationship will allow for a deeper analysis of the pharmaceutical industry, which is characterized by significant differences in how firms different in size tackle R&D investments. Considering the highly skewed distribution of size, we expect to find significant results that will highlight a clear direction of the moderating effect studied.

Hypothesis 2: Firm size has a significant moderating effect on the relationship between market valuation and R&D volatility.

3.3 R&D INTENSITY

The relative amount of R&D has been considered to have a relevant effect on market value in the past literature (Hall et al., 2005). In fact, Galindo-Rueda and Verger (2016) classified the pharmaceutical industry as highly R&D intensive, suggesting it influences the relationship between R&D expenditure volatility and market valuation. Therefore, our study takes this step to fulfill this understanding of the industry. The question that drives this hypothesis is: is the R&D intensity rate relevant for the market valuation of R&D volatility or is the focus on R&D irrelevant? This step can be considered differently from the size approach since it considers a more complex characteristic of the firm. R&D intensity is influenced by many factors, therefore we expect firms with diverse R&D intensity levels to be evaluated differently by the market.

A high level of R&D intensity can signal the firm's commitment to innovation and thus its proactive approach in strengthening its competitive advantage through intellectual properties such as patents. Therefore, this focus on R&D should give the market a positive signal, because the firm should be less interested in overinvesting and poorly managing the projects in place, actively reducing agency issues. However, as mentioned, low levels of R&D intensity have less interest in showing a volatile strategy which investors may value, because the firm's focus is not on the R&D projects in place and volatility is costly. This is because the persistency considered here can be motivated by the high adjustment costs required in volatility (Hall,

2002) and by the history of sunk costs in R&D projects (Máñez et al., 2009). We decide to test this potential moderating effect empirically.

Hypothesis 3: R&D intensity has a significant moderating effect on the relationship between market valuation and R&D volatility.

4. METHODOLOGY

4.1 VARIABLES

The choice of variables has been made following the hypothesis previously stated, considering one common dependent variable, the market value, and different independent variables per hypothesis. Lastly, the model takes into consideration widespread control variables for increased reliability of the results. All the variables have been winsorized at the 1st and 99th percentiles.

4.1.1 Dependent variable

To study the market valuation of firms, the research follows literature on the subject. Tobin's Q ratio is used as a proxy for the market performance of a listed company (Brush et al., 2000; Mudambi and Swift, 2014; Wang et al., 2016). Tobin's Q (TobinQ) has been calculated as the sum of market capitalization and book value of debt divided by the firm's total assets to capture the potential value given by the market to the firm's operations using a relative form, to increase the comparability of results. According to a paper by Lang, Ofek and Stulz (1996), Mudambi and Swift (2014) report that Tobin's Q is generally considered a reliable demonstration for future growth and investment opportunities.

4.1.2 Independent variables

For Hypothesis 1 the main explanatory variable is R&D expenditure volatility. Following Xiang et al. (2020), we set two alternative methods of calculating the main explanatory variable in order to provide a reliable robustness test.

The first method follows a calculation applied by Xiang et al. (2020) using the following formula, where *i* differs per firm and the standard deviation and mean are calculated on a three-

year rolling period, starting from the period 2014, since the first two periods in the sample are used to generate the first useful volatility measure.

$$RDVolatility_{i,t} = \frac{StdDeviation_{i,t}}{Mean_{i,t}}$$

The second alternative method that Xiang et al. (2020) use is the absolute value of the variation in R&D expenses from year to year, which is calculated using the formula below, where *t* goes from the period 2013 to 2022; the first period, 2012, is not considered because it is used as a starting point for the calculation of the following year's volatility.

$$RDChange_{i,t} = \left| \frac{RDExp_{i,t} - RDExp_{i,t-1}}{RDExp_{i,t-1}} \right|$$

For Hypothesis 2, the model introduces an independent variable called size (Size). This variable captures the effect that size has on market valuation of traded companies. It is proxied using the natural logarithm of total assets (Mironiuc et al., 2022), which is a common proxy for this measure. We employ a log-linear model to evaluate the size effect in the regression, in line with other research studies (Mudambi and Swift, 2011), in order to allow the results to capture the partial elasticity of the relationship. In order to capture the difference between market valuation of R&D volatility in large and small firms, the model also includes an interaction term "RDVolatility x Size".

For Hypothesis 3, the model introduces the independent variable R&D Intensity (RDIntensity). It is calculated using R&D expenditures divided by the revenues of the firm, following the Hall et al. (2005) and Mudambi and Swift (2011). This variable captures the focus on R&D in a firm's operations. In order to capture the moderating effect of R&D intensity on the relationship between market valuation and R&D volatility, the model also includes an interaction term, "RDVolatility x RDIntensity".

4.1.3 Control Variables

Following the literature, we include in all models a set of control variables that check for potential effects that influence the market value of firms, reducing the omitted variable bias. We decided to exclude control variables based on revenues, in order to preserve valuable observations that otherwise would have been dropped during the regression.

Leverage (Leverage) is included to check for the debt structure of the firm (Mudambi and Swift, 2014; Wang et al., 2016), and is found as the ratio between long term debt and total assets. Capital Intesity (CAPEXonAssets) is included to check for the share of expenditures dedicated to capital investment each calendar year, and is calculated as the ratio between capital expenditures and total assets. For Hypothesis 3, the capital intensity variable used will be calculated as CAPEX divided by revenues, since in that hypothesis we analyze only firms with revenues different from 0. An alternative proxy for capital intensity (CAPEXyes) will be used in the robustness checks, and it's generated as a dummy that returns 1 if the firm has CAPEX in the period. Selling general and administrative slack is included as a possible explanation of firm performance and is calculated by dividing SG&A expenses over total assets (SGAslack). The choice of using total assets in the ratios follows the need for variables that are less impacted by firm size effects. Size is included as a general control variable. For Hypothesis 3, the net profit margin (NetProfitMargin) will be included in the controls and capital intensity will be described using CAPEX divided by revenues (CapitalIntensity). Moreover, the variables include year controls to check for possible general effects happening on a broader level.

4.2 MAIN MODEL DESCRIPTION

The research will use three different regression models to address the three hypotheses presented in Chapter 3. The dependent variable Tobin's Q is included in the main model, and it will be explained by the independent variable R&D volatility. A set of controls is going to be introduced to check for potential explanations for the dependent variable, and it includes size, leverage, CAPEX over assets, SG&A slack, and ROA. The model's error term captures the effect that cannot be explained by the variables included in the model.

4.2.1 Regression model for effect of R&D volatility on market valuation

The equation used to address Hypothesis 1 is Model 1 and is presented as follows:

$$TobinQ = \beta_0 + \beta_1 RDVolatility + \beta_2 Leverage + \beta_3 CAPEXonAssets + \beta_4 SGAslack + +\beta_5 Size + \beta_6 ROA \quad (1)$$

The effect of R&D volatility on a firm's market value will be captured by coefficient β1. If this coefficient is positive, the market value increase will be partially explained by an increase in R&D volatility, in support of the literature that provides evidence that proactive management of R&D expenses increases the firm's growth (Mudambi and Swift, 2011). A negative

coefficient, on the other hand, would support the opposing idea from Máñez et al. (2009), as reviewed by Kang et al. (2017), in which sunk costs and high adjustment costs resulting from volatility are disruptive to a firm's growth.

4.2.2 Regression model for size moderating effect

Hypothesis 2 will be addressed using the main regression model presented in Hypothesis 1, with the additional variable "R&D Volatility x Size". In this way, the control variable size will be used to understand more deeply the impact of R&D volatility on market value. In order to explain the partial effect of size on R&D volatility, the model also includes the original variables, alongisde with the interaction term. The equation used for Hypothesis 2 is Model 2 and is presented as follows:

$$TobinQ = \beta_0 + \beta_1 RDVolatility + \beta_2 Size + \beta_3 RDVolatility \times Size + \beta_4 Leverage + +\beta_5 CAPEXonAssets + \beta_6 SGAslackAss + \beta_7 ROA \quad (2)$$

If the coefficient β3 returns a result in the opposite direction of the main explanatory variable, then the economic explanation of the relationship would be that larger firms are influenced less by increased R&D volatility, and therefore the market values it less impactfully (Xiang et al., 2020). However, if the coefficient β3 shows a result in the same direction, it would represent the higher influence that R&D expenditure volatility has on the market value of larger firms.

4.2.3 Regression model for R&D intensity

Finally, Hypothesis 3 will be addressed using the main regression model presented in Hypothesis 1, which will take additionally into consideration an interaction term between R&D volatility and R&D intensity. This representation will help explain the potential moderating effect of R&D intensity on the main effect studied. The equation used for Hypothesis 3 is Model 3 and is presented as follows:

$$TobinQ = \beta_0 + \beta_1 RDVolatility + \beta_2 RDIntensity + \beta_3 RDVolatility \times RDIntensity + \beta_4 Leverage + \beta_5 CapitalIntensity + \beta_6 SGAslackAss + \beta_7 NetProfitMargin + \beta_8 ROA \quad (3)$$

If the coefficient β3 returns a result in the opposite direction of the main explanatory variable, then the economic reason behind such an effect would be that the more focused the firm is on

R&D processes, the less the market would be influenced by volatility in R&D expenditures. However, if the coefficient β3 shows a result in the same direction it would mean that high-R&D-intensive firms' market value is more influenced by R&D volatility.

4.3 ESTIMATION METHOD

The empirical analysis in the paper approaches the first model using a multiple linear regression that initially uses ordinary least squares (OLS) estimators to estimate the coefficients.

Fixed effects (FE) and random effects (RE) are considered in the choice for a regression method. The fixed effect method involves including a new factor in the model a_i that captures the time-constant effect, or the time average within each *i* (firm id), and subtracting from the entire model the same time average, obtaining an estimation free of time-constant effects. The random effect method, on the other hand, takes into consideration the time-constant effect ai and assumes that this is uncorrelated to other explanatory variables (Wooldridge, 2018). The study does not preemptively choose one method over the other, therefore a Hausman test has been carried out. We decided not to tackle the endogenity issue in the sample since alternative ways to deal with endogeneity were found to be weak or of difficult application in our sample, following Wang et al. (2016).

Serial correlation is another problem that frequently affects data in panel data analyses. Our sample, consisting of different firms and multiple year observations per firm, cannot be considered unaffected by this issue. Therefore, in order to limit its potential disruptive effect on reliability of data, the estimation is going to be carried out using clustered robust standard errors by sub industry, following the 4-digits SIC codes assigned. This will allow the estimation to be more robust at the sub industry level.

Since heteroskedasticity is a common issue among panel data analyses (Kang et al., 2017), the research runs, among the pre-regression diagnostic tests, a White test for heteroskedasticity.

5. DATA AND SUMMARY STATISTICS

5.1 SAMPLE CONSTRUCTION

The data has been gathered using the S&P Capital IQ database as a source of information. We decided to choose S&P Capital IQ because of the amount of data available and their reliability. Our sample consists of firms publicly traded on all the U.S. exchanges, both as primary and

secondary listings, between the years 2012 and 2022. To filter for the industry, we used Capital IQ's classification of the "Pharmaceuticals, Biotechnologies, and Life Sciences" sector, which includes SIC codes 2800, 2833, 2834, 2835, 2836, 3826, 3841, 3845, 8731, and 8734 as main subsectors (Table 1). The idea of including biotechnologies and life sciences in addition to the only pharmaceutical industry was made following Mironiuc et al.'s (2022) approach. They include pharmaceuticals, biotechnologies, and medical research industries in the European market, and this addition was considered appropriate based on the many analogies between these industries.

The sample retrieved from Capital IQ consisted of data from 1708 firms (Table 1). As a last step in the filtering, the data was cleared of observations with missing values in any of the variables. Moreover, we dropped observations with total assets equal to 0, because the dependent variable uses this measure as the denominator in its calculation and therefore the missing values would have been automatically dropped in the regressions. The final sample consists of annual data points for the calendar years 2012–2022, which were obtained from 870 different firms, adding up to 4346 firm-year data.

The sample for the hypothesis researching the moderating effect of R&D intensity on the relationship between R&D volatility and market value (Hypothesis 3) is limited in relation to the complete sample. This happens because revenues are present in the denominator, generating a ratio that would give a missing value if the revenue used was equal to 0. In the pharmaceutical industry representation in our sample, we found that it is common for small firms to have zero revenues for the first years, even though there is R&D in place; therefore, we acknowledge this limitation in the sample, and accept the final sample for Hypothesis 3 of 643 different firms and 3121 firm-year data.

5.2 DESCRIPTIVE STATISTICS AND CORRELATION ANALYSIS

5.2.1 Summary statistics

Table 2 summarizes the descriptive statistics of the variables used in the different models and hypotheses. Tobin's Q has a mean value of 6.339 in the sample, meaning that the overall consideration of the market is positive and the market recognizes value of growth opportunities and future investment that are potentially higher than the assets in place. Tobin's Q standard deviation shows that data are dispersed in relation to the average.

R&D volatility measures have, by nature, less observation, based on the fact that there is a minimum amount of time required to create such a variable. Moreover, firms that consistently have R&D expenses equal to 0 are automatically dropped from the volatility calculation. Considering the strong outliers issue in the sample regarding the R&D volatility measure, we decide to further winsorize the variable. The main problem lies in the upper part of the sample, where many observations present extreme values. Therefore we winsorize the RDVolatility at the 5th and 90th percentile, in this way the weight of outliers is reduced and it does not affect the calculations. The mean volatility in the sample is 0.395 for a 3-year rolling period. The volatility captured by the alternative calculation RDChange is equal to 0.557.

Leverage has a mean value of 0.178, meaning that pharmaceuticals, biotechnologies, and life sciences are generally low-levered. Size takes both positive and negative values since it's calculated as the natural logarithm of total assets. R&D intensity has a mean of 0.781, meaning that firms in the sample are highly reliant on R&D investments. CAPEX over assets, on the other hand, has a mean value of 0.019, showing that pharmaceutical firms in the sample retrieved have generally low capital expenditures. SG&A over Assets has a mean value of 0.609, meaning that pharmaceutical firms have high needs for general, selling and administration costs.

5.2.2 Subindustry summary statistics

Table 3 shows the list of all subindustries included in the sample, dividing firms by the assigned 4-digits SIC codes for their primary industry. By observing the frequency of the subindustries it's clear that the most common ones are 2836, 2834, 2835, 3826, and 8731, which constitute more than 90% of the sample. In the same table are also presented the average measures for Tobin's Q and R&D volatility. Observing the main subindustries, in comparison to the general mean values for Tobin's Q of 6.339 and for R&D volatility of 0.395, it's possible to point out that "Pharmaceutical Preparations" firms (2834) are generally valued less by the market, that assigns a mean Tobin's Q of 4.15; "Biological Products" (2836) and "In Vitro and In Vivo Diagnostic" (2835) are, on the other hand, generally highly valued by the market. This difference in more weakly observable in the R&D volatility means; they present all similar values, in line with the general mean, however "Pharmaceutical Preparations" firms (2834) have in average a lower volatility than "Biological Products" (2836) and "In Vitro and In Vivo Diagnostic" (2835). Such a difference is explained by the market trend of the moment, by the

frontier of research in that specific subindustry, and by the growth opportunities perceived by the market in their field of research.

5.2.3 Correlation analysis

The correlation analysis between variables has been carried out and results are shown in the pairwise correlation matrix in Table 4. The matrix shows the correlation and the statistical significance of each pair of variables. There are no variables that have a coefficient higher than 0.5, therefore decreasing the chance for multicollinearity in the sample (Hai et al., 2019). We find a weak positive correlation between Tobin's Q and R&D volatility.. Size has a negative correlation with Tobin's Q, in line with expectations. Analyzing the correlation for other variables, it's possible to point out the generally higher correlation between size and R&D volatility, between R&D intensity and size, and lastly, between R&D intensity, ROA, capital intensity and net profit margin, which is caused by the fact that their calculations depend directly on revenues.

6. RESULTS

6.1 HAUSMAN TEST AND WHITE TEST

The null hypothesis considered in the Hausman test is that there is no correlation between explanatory variables and the error term, and therefore the random effect model is preferred. The alternative hypothesis is that there is a potential correlation; therefore, the time-constant effect has to be demeaned and the fixed effect is preferred (Wooldridge, 2018). The findings of the Hausman test (Table 5) depict a P-value of 0.081, which allows us to reject the null hypothesis at a 0.1 significance level, and therefore prefer the fixed effects model. For completion of the analysis, the random effects model is also included in the first hypothesis results.

The White test is used to check for potential heteroskedasticity in the sample. The findings of the White test (Table 6) indicate that we cannot reject the null hypothesis H_0: Homoskedasticity at a 0.1 significance level. Therefore, it provides evidence towards homoskedasticity in the sample. Although the heteroskedasticity problem is reliably addressed by the White test, it is

impossible to fully validate the homoskedasticity of the data. Nevertheless, heteroskedasticity is not considered a significant issue in the sample (Wooldridge, 2018).

6.2 REGRESSION MODELS' ANALYSES

6.2.1 Regression results for relationship between R&D volatility and market value

The estimations for the models reflecting Hypothesis 1 are displayed in Table 7 along with the findings. The study uses an OLS estimation with firm fixed effects and default standard errors in Column 1. It employs GLS estimators with random effects and default standard errors in Column 2. Column 3 and 4 repeat the previous models, using instead of default standard errors the more appropriate clustered standard errors. In this case, the clustering of standard errors was grouped by sub industries. Regression accounts for year effects in all four models. Industry controls are automatically omitted due to collinearity in the fixed effects model, and are included in the random effects model. The dependent variable is Tobin's Q (TobinQ), and the main explanatory variable is R&D volatility (RDVolatility).

In the models presented in column 1 and 2, R&D volatility has an important positive effect on Tobin's Q, however it is not statistically significant. Observing the more reliable results using standard errors clustered by subindustry, we recognize a relevant increase in statistical significance. The p-value for RDVolatility in column 3 allows us to reject the null hypothesis. In the case of our preferred model using fixed effects, an increase in the volatility of R&D expenditures of 1% would generate an increase in Tobin's Q of 2.206%, leading to a positive consideration of R&D volatility by the market. This effect is economically significant, since an increase of 2.206% percent in Tobin's Q can be considered highly valuable for firms that rely on future growth opportunities. The coefficient explains how the "Firm A", which has an R&D volatility of 1% more than "Firm B", ceteris paribus, is expected to have a Tobin's Q 2.21% higher than "Firm B", meaning that the market value is increased by a higher R&D volatility.

The findings support the working hypothesis that R&D volatility has a significant effect on market valuation. The positive effect that we find can be explained, in the specific case of the pharmaceutical industry, by proactive management. Meaning that, a higher volatility in the R&D expenditures is a proxy for a more active management of the investments, which are more likely to vary and dynamically change. Managers in this case are not influenced by the presence of sunk costs (Máñez et al., 2009) or high adjustment costs (Bernstein and Nadiri,

1989), and are therefore not held back by these considerations in the decisions on better R&D opportunities. The proactive management is perceived by the market as the signal for quality of R&D management, which means that managers recognize the potential failure of R&D projects and are less prone to overinvestment in failing projects. Based on the signaling theory, proactive management can be considered a signal for a reduced agency issue in the firm, since it carries the characteristics of a signal, by being costly, observable and verifiable by the market (Spence, 1973), and limits the risk of managerial myopic behavior.

The bottom-line objective of signaling theory is to reduce information asymmetry, in this case between investors and management, which leads to a better understanding of the firm by the market and an alignment of contractual power (Spence, 2002). The investors, after having recognized the proactive management of the firm, are left with more insights on the benefits and risks of the R&D in process, and are more willing to increase the market value of such a firm. If the reasons behind the volatility are known to the market, the effect of R&D volatility is positive for firms that operate in a very R&D active industry (Aboody and Lev, 2000).

The direction of the effect is coherent with current literature. According to Hai et al.'s (2019) study, a significant positive relationship between R&D volatility and market value was found using multiple regression methods. Market value can be influenced by many different factors, which cannot always be directly observed due to being intangible or difficult to quantify, such as intellectual property or even employee talent, as Bernstein and Nadiri (1989) consider. They underline the dependency of employee talent on R&D investments, which validates the difficulty in quantifying certain factors influencing market valuation. Nevertheless, the R&D volatility can be quantified and consequently analyzed. R&D volatility can be affected by the heterogeneity of R&D activities, which can give a competitive advantage, as suggested by Xiang et al. (2020), and therefore result in higher market share. For instance, successful R&D projects can result in intellectual property rights in the form of patents, which can be considered by the market as a costly quality signal. This can make such firms more profitable and subsequently increase their market valuation.

Considering the control variables, the estimation using clustered standard errors finds statistical significance for Size and SGAslack. Size has a negative effect on Tobin’s Q, reflecting the decrease in growth opportunities for larger firms, as supported by Demirel and Mazzucato (2012). While studying publicly listed US pharmaceutical companies between 1950 and 2008, they highlight that large pharmaceutical firms experience reduced growth opportunities when

increasing R&D expenditure (Demirel and Mazzucato, 2012). On the contrary, small firms that practice persistent patenting for at least five years boost their growth opportunities with R&D spending (Demirel and Mazzucato, 2012). SG&A over assets is positively related to Tobin's Q, reflecting that the flexibility of the cost structure is positively viewed by the market, and its effect is in line with literature findings (Nason and Patel, 2016). Finally, CAPEX over assets has a very strong negative impact on Tobin's Q, however its result is not statistically significant while using clustered standard errors. This relationship is in line with the expected effect of capital expenditures on market valuation (Hai et al., 2019).

6.2.2 Regression results for moderating effect of size

Table 8 shows the results of the estimations for the models representing Hypothesis 2. In Column 5, the research employs an OLS estimation with a fixed effects model and default standard errors. In Column 6, GLS estimates are used with random effects and default standard errors. In Column 7 and 8 the fixed effects and random effects models are replicated using robust standard errors clustered by subindustry. In all models, the regression controls for year effects and industry controls are automatically omitted for collinearity in the fixed effects models. The dependent variable is Tobin's Q, and the explanatory variables are R&D volatility and size. In addition, an interaction term between R&D volatility and size is included.

In column 5 the coefficient explaining the effect of R&D volatility on Tobin's Q is not statistically significant. The size effect results in a negative effect on Tobin's Q that is strongly statistically significant. The interaction term is not statistically significant on a 0.1 significance level. In column 6, using random effects, the two main explanatory variables and the interaction term acquire statistical significance, presenting a negative coefficient on the interaction term.

In column 7 and 8, using standard errors clustered by subindustry, the results remain consistent with the non-clustered models in column 5 and 6, maintaining statistical and economic significance on the coefficients that were previously significant. Observing the random effects model's results, the partial effect captured by the combination of R&D volatility and size communicates that as size increases, the R&D volatility effect on Tobin's Q is proportionally reduced, in line with expectations (Xiang et al., 2020). This negative effect explains the increased magnitude of the partial effect of R&D volatility compared to the Model 1 results.

The findings from the fixed effects models do not provide enough evidence to draw strong conclusions on the moderating effect of size on the relationship between R&D volatility and

Tobin's Q. However, drawing from the results estimated using random effects, the statistical significance makes it possible to observe a negative coefficient in the interaction term with a magnitude of -0.799. This implies that, ceteris paribus, an increase of 1% in size would generate a partial negative effect of -0.799% on Tobin's Q. Economically, this means that larger firms are less affected by R&D volatility in our sample. To explain this phenomenon, we draw from the theory to help us analyze the market valuation of firms based on their size. Once again, we propose again the argument presented in section 6.1.1 on the analysis of the relationship between R&D volatility and market valuation, according to which R&D volatility affects positively the market valuation of pharmaceutical firms. Then we take a further step in the analysis and consider the effect of size. As size increases in pharmaceutical firms, the absolute value of R&D investment increases, and a less scattered volatility is expected due to the larger number of projects in place (Xiang et al., 2020). The increase in R&D investments leads the market to carefully analyze possible R&D changes in large firms, which could be motivated by potential earnings management practices or disruptive effects of more R&D projects being suspended or shut down (Xiang et al., 2020). Therefore the market perceives this new information as a signal of value-reducing practices, and adjusts its valuation negatively.

Another explanation could be the availability of firm information in large firms. According to Aboody and Lev (2000), firm size is a reliable proxy for information asymmetry, and therefore the decreased effect of R&D volatility on Tobin's Q caused by size can be related to the fact that, opposed to smaller firms, larger firms have a higher information asymmetry level, perhaps due to the loss in corporate control. This means that the gap filled by data on R&D volatility is not enough to reduce the information asymmetry, and therefore the market is not as influenced as it should be by R&D volatility in large firms.

Consistent with our results, current literature finds statistically significant results for this hypothesis, providing a similar explanation in terms of direction of the effect. As firm size grows, Xiang et al. (2020) anticipate that R&D volatility will negatively affect returns. Managers engaging in earnings management resulting in overinvestment is a possible explanation for this market response (Xiang et al., 2020). Furthermore, Li's (2011) positive assumption between R&D expenditure and return is reflected in smaller firms, suggesting that R&D expenditure is generally value-adding for said firms. Contrary to the negative R&D volatility-return relationship of large firms, smaller firms do not experience the same market reaction. A governance mechanism restricting overinvestment in R&D by technocrats is a potential rationale suggested by Xiang et al. (2020).

Contrary to findings from Xiang et al., (2020), but still in line with our hypothesis, Mudambi and Swift (2011) suggest that the link concerning R&D volatility and performance is weaker for smaller firms. Lubatkin et al. (2006) reason that smaller firms lack both facilitating resources and slack resources to move between the exploitation and exploration processes in their R&D activities to satisfy external market conditions. This leaves smaller firms no choice but to specialize in either exploitation or exploration, and hence, R&D volatility for such firms may contribute to lower performance, as Beckman (2006) and Mudambi and Swift (2011) suggest. This could be because smaller firms tend to be more entrepreneurial, and a shift from explorative R&D activities towards exploitative activities may be seen as a loss in specialization (Reinganum, 1983).

Considering the control variables, only SG&A slack provides statistically significant results, in a similar effect compared to Model 1. Other controls did not find statistically significant results.

6.2.3 Regression results for moderating effect of R&D intensity

Table 9 presents the results together with the estimations for the models tackling Hypothesis 3. The research used an OLS estimation in Column 9, coupled with a fixed effects model and default standard errors. Column 10 uses GLS estimators with random effects and default standard errors. Column 11 and 12 replicate the fixed effects and random effects models using standard errors clustered by subindustry. In all models, regression takes year effects into account and industry controls are automatically omitted for collinearity in the fixed effects models. The dependent variable is Tobin's Q, and the explanatory variables are R&D volatility and R&D intensity. In addition, an interaction term between R&D volatility and R&D intensity is included. This model has an implied limited sample, caused by the reduced number of firms having revenues greater than 0. Therefore, it is not deemed necessary to exclude the control variables based on revenues, which would have harmed the previous models, so CapitalIntensity is included in place of CAPEXonAssets for capital intensity and net profit margin (NetProfitMargin) is included as control.

In the two default standard errors models, no main explanatory variable is statistically significant. The only explanatory variable that acquires significance in the random effects model is R&D intensity. All other results remain consistently insignificant in the two models that use standard errors clustered by subindustry. The lack of statistical significance in all the explanatory variables raises questions about the design of the hypothesis and of the model. A

possible explanation for the loss of significance in the variables is the limited sample used in this hypothesis, which could be harmful for the reliability of the estimation.

The results do not support our third hypothesis, stating that R&D intensity has a significant moderating effect on the relationship between Tobin's Q and R&D volatility. The observable effect is that the interaction term between R&D volatility and R&D intensity is not perceived by the market in a significant way. In the specific case of this sample, the market takes into consideration other factors when evaluating firms, and therefore the hypothesis should be approached differently in future research. This could mean including other or more relevant variables. Another explanation for the lack of significance is the potential serial correlation in the sample, which is disrupting the results. In support of this point, when using clustered standard errors instead of the default ones, the p-values for the main explanatory variables decrease. Clustered standard errors are, in fact, a reliable method to address serial correlation.

However, in order to show that R&D intensity and R&D volatility remain significant even in the limited sample, we run an additional regression omitting the interaction term. Results show in Column 13 that R&D volatility is statistically significant and in line with previous analyses' findings, and R&D intensity has a statistically significant positive effect on Tobin's Q, with a coefficient of 0.935 (Table 9). Therefore, a further explanation is that both R&D volatility and R&D intensity are independently significant on Tobin's Q, hinting that the interaction term in the model does not add any additional explanation. This is supported by the very low correlation observable in the correlation matrix (Table 4).

Following these findings, we explore the idea that R&D intensity and R&D volatility do not have an effect on each other. This point is supported by the evidence that the two variables provide different explanations for firm performance (Mudambi and Swift, 2011). R&D intensity is found as a proxy for firm dedication in R&D investments (Hall et al., 2005) and R&D volatility is considered as a signal for the quality of R&D management, as it indicates proactive management (Mudambi and Swift, 2011). Since they provide different information to the market, there is limited evidence that supports the idea that information asymmetry is reduced by analyzing the interaction of the two variables.

Supporting our analysis, Mudambi and Swift (2011) show a weak relationship between R&D intensity and R&D expenditure volatility. Currently, there is no further literature discussing the relationship between market valuation and R&D volatility, moderated by R&D intensity. However, Jiang et al. (2021) propose a negative correlation between R&D-intensive firms and

their share price as a means to alleviate shareholders risk exposure in financially constrained firms. Mazzucato and Tancioni (2012) oppose this by suggesting that greater disclosure of information in these firms allows investors to make informed judgments about R&D investment risk. However, the literature investigates the relationship between market valuation and R&D intensity, but not market valuation and R&D volatility moderated by R&D intensity. Regarding the control variables, the only consistently significant variable is SG&A slack, which does not provide any additional insight on the researched hypothesis.

6.3 ROBUSTNESS CHECKS

6.3.1 R&D volatility alternative

As a final step in the results analysis, we test one different measure for the main explanatory variable. The alternative measurement of R&D volatility has been used by Xiang et al. (2020) and calculated as an absolute value of the change in R&D expenditures from year to year. The research uses this alternative variable to re-estimate the previous models using fixed effects. Results presented in Table 10 provide statistically significant coefficients in line with previous findings, excluding the Model 2 coefficient. The direction of the variable coefficient is positive, however the magnitude changes due to the different nature of the variable, which is calculated in a different way and therefore captures the effect differently. This finding shows robustness in the main explanatory variable, and is consistent with the information asymmetry argument previously presented.

6.3.2 CAPEX intensity alternative

A proxy measure is also used instead of capital intensity. Using a dummy variable (CAPEXyes) that returns 1 if the firm has capital expenditures and 0 otherwise can provide a valuable robustness test for the control variable CAPEXonAssets. Results presented in Table 11 Column 17 for Model 1 are generally consistent, even though the proxy measure used does not provide a significance level under 0.1.

6.4 LIMITATIONS OF THE STUDY

Our study is based on data gathered from Capital IQ, therefore the chances that errors in the data sample impacting our results are not to be excluded. Another bias encountered during the research has been the calculation bias of the main explanatory variable RDVolatility, which presented a very skewed distribution with a great number of outliers. This was handled by winsorizing at larger percentiles. However, a possible explanation for the bias in the outliers

weight is the 3 year period used in the calculation, which could be increased to provide a less scattered, and less extreme volatility measure.

Another possible limitation of our study is the time period from 2012 to 2022, since in a longer time period more observations would have been available. Perhaps, an extended time period would provide a higher chance of finding statistically significant results. Moreover, the sample size could be increased by expanding the number of industries considered. However, the latter solution defeats the point of our motivation, supported by Kang et al.'s (2017) idea of heterogeneous R&D investments across industries. In fact, our motivation is based on the analysis of the pharmaceuticals, biotechnologies and life sciences industry, to gather specific results on their R&D market valuation.

A final limitation, and possible cause of bias is endogeneity. Since it has not been directly addressed, we cannot fully guarantee that our results are reliable, mainly on the possible causality bias. It is possible for our dependent and explanatory variables to be unclear in the direction of causality and we therefore suggest future research to address this issue and take actions to solve it.

7. CONCLUSION

Our findings contribute to the field of research by addressing an unclear literature stance on the R&D volatility effect by focusing on the pharmaceutical industry. These results and their economic interpretation are expected to provide more context and empirical research to stakeholders. Among others, investors, professional analysts and industry decision-makers are the main targets of our findings, since they are responsible for the market valuation and firms' policy making decisions. The positive outlook of proactive management considered in the analysis leads to a more favorable view of R&D expenditure volatility, which is supposed to discourage managerial myopic behavior. Therefore as a general stance, the stakeholders that we addressed, should view R&D expenditure volatility favorably given its positive relationship with firm market value. However, size is a factor that must be taken into consideration, since larger firms have different stakeholders and their interests are more heterogeneous.

The purpose of empirical research is to analyze the effect that volatility in R&D expenditures has on market valuation in pharmaceutical, biotechnology, and life sciences firms publicly

traded on all U.S. exchanges, and the moderating effects of size and R&D intensity. Findings suggest that the volatility of R&D expenditures has a significant positive effect on a firm's relative market valuation, proxied by Tobin's Q, supporting Hypothesis 1. Theoretical literature helps clarify this result, giving different explanations for the positive relationship found, and Mudambi and Swift (2011) provide valuable empirical research in support. The volatility of R&D is often related to proactive management, and the possibility of having a dynamic approach to R&D investments allows firms to exploit valuable R&D progress and reduce overinvestment in failing R&D projects, which signals the market about the quality of management. This signal is used by the market to reduce the information asymmetry gap and gain a deeper understanding of benefits and risks of unobservable R&D projects. Relevance of information asymmetry is stressed particularly in an R&D-intensive industry, such as pharmaceutical, biotechnologies and life sciences (Aboody and Lev, 2000). Since the increase in Tobin's Q reflects future growth possibilities, increased R&D volatility has been found to boost opportunities for pharmaceutical firms (Kang et al., 2017).

Additionally, the analysis of the results provided support for the moderating effect that firm size has on the relationship between R&D volatility and market valuation, finding that size has a negative effect on how the market considers R&D volatility. For larger firms, R&D volatility is not as value-adding as in smaller firms. The reason behind this effect can be explained by drawing from agency theory and information asymmetry. Given that larger firm's R&D investments are greater, in absolute numbers, the R&D projects in place are expected to be more, and therefore the chance for managers (agents) to engage in disruptive actions such as earnings management is greater (Xiang et al., 2020). In addition, more projects entail higher information asymmetry, signaling that the effectiveness of R&D volatility to minimize the knowledge gap decreases. As a result, the market has less consideration for the effect that volatility has on firm market value in larger firms. Literature is also divided on the findings about this relationship; however, in the specific case of the pharmaceutical industry, our results are supported by findings from Li (2011), which suggest that R&D expenditures are normally more value-adding for smaller firms since they have the possibility to scale their operations and meet new growth opportunities.

Lastly, the research approaches a third hypothesis with the objective of providing evidence for the significant moderating effect of R&D intensity on the relationship between R&D volatility and market performance. Our results fail to find any statistical significance from the regression estimation of the interaction between the two explanatory variables. However, we find

significant results when individually including such variables, and therefore our analysis states that the two have independent effects on Tobin's Q, but have no shared effect. Considering that we relate the significant effect of R&D volatility and R&D intensity to a reduction of information asymmetry and potential growth opportunities, the lack of significance in the interaction provides no support for the hypothesis that intensity has a moderating effect on the relationship. This finding is supported by the idea, from Mudambi and Swift (2011), that R&D volatility and intensity provide different explanations for firm performance, and therefore, they are not considered simultaneously in the market analysis. Mudambi and Swift (2011) also reached a similar conclusion, showing a weak relationship between R&D intensity and R&D volatility. It should not be excluded that problems might have arisen from the peculiar composition of our sample, consisting of a relevant share of firms without revenues. We suggest that future research on this matter focus on a different interpretation of R&D intensity, which could be observed using a different proxy or through a more industry-specific metric. Following Mudambi and Swift's (2014) approach, by considering the difference between positive and negative R&D volatility and applying it to the pharmaceutical industry could give deeper insights on the market valuation of future opportunities. To expand on our research, we suggest widening the sample to different geographical areas or by comparing parallel analyses on different industries in order to deepen the understanding of R&D investments and be able to provide more reliable insights for stakeholders and professionals to base their valuation on.

TABLES

Table 1 - Sample creation process

The table gives indications for the sample selection process, presenting how many firms composed the initial dataset retrieved from Capital IQ. It doesn't take into account the loss of firms (and observations) due to missing values.

Filters	*Number of firms*
Exchange country/region: United States	*22152*
Pharmaceuticals, Biotechnologies and Life Sciencies	*1708*

Table 2 – Descriptive summary statistics

The table includes all the variables included in the three main hypotheses. The loss of observations in RDIntensity, NetProfitMargin and CapitalIntensity is due to the fact that these calculations rely on revenues as a denominator, and in the sample a relevant part of the firm year observations has revenues equal to 0. RDChange has also less observations because it based on a calculation where the requirement is two valid results consecutively. The statistics presented are number of observations, mean, standard deviation, minimum value, and maximum value.

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
TobinQ	*4346*	*6.339*	*47.351*	*.103*	*2727.357*
RDVolatility	*4346*	*.395*	*.313*	*0.38*	*1.007*
Size	*4346*	*4.64*	*2.718*	*-2.303*	*11.239*
CAPEXonAssets	*4346*	*.019*	*.041*	*0*	*.71*
CAPEXyes	*4346*	*.697*	*.459*	*0*	*1*
SGAslackAss	*4346*	*.609*	*2.425*	*.002*	*80*
Leverage	*4346*	*.178*	*.669*	*0*	*15*
ROA	*4346*	*.285*	*.486*	*0*	*12*
RDIntensity	*3121*	*.781*	*1.127*	*0*	*7.829*
NetProfitMargin	*3121*	*-15.658*	*100.478*	*-3491*	*219.333*
CapitalIntensity	*3121*	*.342*	*2.459*	*0*	*102*
RDChange	*4082*	*.557*	*2.271*	*0*	*92.266*

Table 3 – Subindustry summary – including average of Tobin's Q and R&D volatility

The table presents summary statistics per subindustry, using the 4-digits SIC classification to divide each subsector. This table is aimed at showing the frequency of each in the sample, providing statistics and a better understanding of the intricated division of subindustries. Some of the industries present are not completely related to the macro pharmaceutical industry. This happens because of CapitalIQ "industry classification" definition which could show instead of the primary SIC code, a co-primary code. However, all the firms included have among their industry classification codes one of the main pharmaceutical ones.

SIC Codes (Primary)	Freq.	Percent	Cum.	TobinQ_mean	RDVolatility_mean
0100 Agricultural Production Crops	3	0.07	0.07	5.26	.83
1000 Metal Mining	3	0.07	0.14	52.69	1.01
2084 Wines, Brandy	2	0.05	0.18	2.09	1.01
2090 Miscellaneous Food Prep	8	0.18	0.37	.79	.57
2800 Chemicals and Allied Products	25	0.58	0.94	2.30	.34
2830 Drugs	10	0.23	1.17	5.75	.23
2833 Medicinal Chemicals	50	1.15	2.32	3.35	.38
2834 Pharmaceutical Preparations	1461	33.62	35.94	4.15	.39
2835 In Vitro and In Vivo Diagnostic	163	3.75	39.69	11.03	.42
2836 Biological Products	2275	52.35	92.04	7.80	.41
2870 Agricultural Chemicals	5	0.12	92.15	1.62	.21
3060 Fabricated Rubber Products	9	0.21	92.36	4.97	.08
3220 Glass And Glassware	3	0.07	92.43	1.25	0.79
3523 Farm Machinery	4	0.09	92.52	1.11	0.86
3559 Special Industry Machinery	2	0.05	92.57	1.95	1.00
3821 Laboratory Apparatus	8	0.18	92.75	6.84	.72
3826 Laboratory Instruments	139	3.20	95.95	3.60	.15
3841 Surgical Apparatus	6	0.14	96.09	15.36	.69
3842 Surgical Appliances	17	0.39	96.48	9.80	.36
3845 Electromedical Apparatus	17	0.39	96.87	4.20	.44
4899 Communications Services	1	0.02	96.89	6	0.03
5122 Drugs, Drug Proprietaries	5	0.12	97.01	.73	0.89
5159 Farm-Product Raw Materials	2	0.05	97.05	3.44	1.01
7370 Computer Programming, Data	1	0.02	97.08	.47	.87
8071 Medical Laboratories	7	0.16	97.24	4.74	.33
8731 Biological Research	120	2.76	100.00	3.74	.40
Total	4346	100.00			

Table 4 – Pairwise correlation matrix

The table shows the pairwise correlation matrix among all relevant variables included in the regression models. It shows that none have a coefficient greater than 0.5, meaning that collinearity is limited.

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
(1) TobinQ	*1.000*											
(2) RDVolatility	*0.059***	*1.000*										
(3) Size	*-0.158***	*-0.349***	*1.000*									
(4) Leverage	*0.076***	*0.034***	*-0.083***	*1.000*								
(5) CAPEXonAssets	*-0.017**	*0.025**	*-0.002*	*0.012*	*1.000*							
(6) SGAslackAss	*0.137***	*0.144***	*-0.182***	*0.071***	*-0.011*	*1.000*						
(7) ROA	*0.016*	*-0.075***	*0.033***	*0.141***	*0.045***	*0.078***	*1.000*					
(8) RDIntensity	*-0.006*	*-0.039***	*-0.162***	*-0.027***	*-0.074***	*-0.016*	*-0.201***	*1.000*				
(9) NetProfitMargin	*-0.001*	*-0.040***	*0.043***	*0.005*	*0.014*	*-0.003*	*0.105***	*-0.359***	*1.000*			
(10) CapitalIntensity	*-0.003*	*0.073***	*-0.001*	*-0.004*	*0.209***	*-0.012*	*-0.044***	*0.136***	*-0.325***	*1.000*		
(11) RDChange	*0.008*	*0.285***	*-0.079***	*-0.006*	*-0.009*	*0.014*	*-0.046***	*0.044***	*-0.014*	*0.003*	*1.000*	
(12) CAPEXyes	*-0.112***	*-0.215***	*0.579***	*-0.062***	*0.267***	*-0.114***	*0.062***	*-0.115***	*0.016*	*0.040***	*-0.075***	*1.000*

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5 - Hausman test results

The table shows the summary of the results from the Hausman test, indicating the the p-value on which we draw conclusions and decide to reject the null hypothesis.

Hausman (1978) specification test

	Coef.
Chi-square test value	*21.89*
P-value	*.0809*

Table 6 - White test results

The table includes a summary of the White's test carried out, including the p-value on which we draw conclusion and decide to not be able to reject the null hypothesis.

White's test

H0: Homoskedasticity

Ha: Unrestricted heteroskedasticity

chi2(83) = 53.33

Prob > chi2 = 0.9954

Cameron & Trivedi's decomposition of IM-test

chi2	*df*	*p*
53.330	*83*	*0.995*
11.260	*14*	*0.666*
1.030	*1*	*0.309*
65.620	*98*	*0.995*

Table 7 – Regression results for relationship between R&D volatility and market value

The table shows the results from the first hypothesis, including estimations of Model 1 using: OLS with fixed effects, year controls in column 1 and 3, and GLS with random effects, year controls, industry controls in column 2 and 4. Column 1 and 2 employ default standard errors. Column 3 and 4 employ standard errors clustered by subindustry.

	(1)	(2)	(3)	(4)
	Model 1	Model 1	Model 1	Model 1
VARIABLES	TobinQ	TobinQ	TobinQ	TobinQ
RDVolatility	2.206	2.191	2.206**	2.191
	(2.985)	(2.684)	(1.066)	(1.689)
Size	-4.042***	-2.491***	-4.042***	-2.491**
	(1.098)	(0.596)	(1.100)	(1.193)
CAPEXonAssets	-52.407***	-36.166**	-52.407	-36.166
	(19.029)	(17.746)	(47.860)	(30.899)
Leverage	-0.126	0.172	-0.126	0.172
	(1.402)	(1.228)	(0.759)	(0.894)
SGAslackAss	2.243***	2.337***	2.243***	2.337***
	(0.403)	(0.355)	(0.262)	(0.230)
ROA	0.446	0.285	0.446	0.285
	(3.088)	(2.173)	(0.889)	(0.804)
Constant	22.683***	14.986	22.831***	14.986**
	(6.012)	(10.653)	(5.949)	(7.061)
Year Controls	Yes	Yes	Yes	Yes
Industry Control	No	Yes	No	Yes
Fixed Effects	Yes	No	Yes	No
Standard errors	Default	Default	Clustered by subindustry	Clustered by subindustry
Observations	4,346	4,346	4,346	4,346
R-squared	0.025		0.025	
Number of firmid	870	870	870	870

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

Table 8 – Regression results for moderating effect of size

The table shows the results from the second hypothesis, including estimations of Model 2 using: OLS with fixed effects, year controls in column 5 and 7, and GLS with random effects, year controls, industry controls in column 6 and 8. Column 5 and 6 employ default standard errors. Column 7 and 8 employ standard errors clustered by subindustry.

	(5)	(6)	(7)	(8)
	Model 2	Model 2	Model 2	Model 2
VARIABLES	TobinQ	TobinQ	TobinQ	TobinQ
RDVolatility	3.389	6.394	3.389	6.394*
	(4.713)	(4.316)	(2.213)	(3.748)
Size	-3.905***	-2.096***	-3.905***	-2.096**
	(1.177)	(0.673)	(0.962)	(0.954)
RDVolatilityxSize	-0.233	-0.799	-0.233	-0.799*
	(0.718)	(0.643)	(0.244)	(0.440)
CAPEXonAssets	-52.253***	-35.475**	-52.253	-35.475
	(19.037)	(17.754)	(47.818)	(30.842)
Leverage	-0.138	0.101	-0.138	0.101
	(1.402)	(1.229)	(0.769)	(0.930)
SGAslackAss	2.232***	2.281***	2.232***	2.281***
	(0.404)	(0.357)	(0.270)	(0.255)
ROA	0.457	0.137	0.457	0.137
	(3.089)	(2.174)	(0.879)	(0.875)
Constant	21.935***	12.882	22.155***	12.882**
	(6.439)	(10.754)	(5.299)	(5.901)
Year Controls	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	No	Yes
Fixed Effects	Yes	No	Yes	No
Standard errors	Default	Default	Clustered by subindustry	Clustered by subindustry
Observations	4,346	4,346	4,346	4,346
R-squared	0.025		0.025	
Number of firmid	870	870	870	870

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

Table 9 – Regression results for moderating effect of R&D intensity

The table shows the results from the third hypothesis, including estimations of Model 3 using: OLS with fixed effects, year controls in column 9, 11 and 13, and GLS with random effects, year controls, industry controls in column 10 and 12. Column 9 and 10 employ default standard errors. Column 11, 12 and 13 employ standard errors clustered by subindustry. Column 13 estimates a variation of Model 3 that does not include the interaction term.

	(9)	(10)	(11)	(12)	(13)
	Model 3	Model 3	Model 3	Model 3	Model 3-alt
VARIABLES	TobinQ	TobinQ	TobinQ	TobinQ	TobinQ
RDVolatility	3.266	4.301	3.266	4.301	2.371**
	(4.483)	(4.046)	(2.240)	(3.401)	(1.019)
RDIntensity	1.485	0.291	1.485	0.291	0.935*
	(2.159)	(1.852)	(1.088)	(0.212)	(0.483)
RDVolatilityxRDIntensity	-1.218	-1.694	-1.218	-1.694	
	(3.247)	(3.022)	(1.340)	(1.369)	
CapitalIntensity	-0.505	-0.228	-0.505	-0.228**	-0.509
	(0.622)	(0.450)	(0.411)	(0.112)	(0.397)
NetProfitMargin	-0.000	-0.003	-0.000	-0.003*	-0.001
	(0.011)	(0.011)	(0.001)	(0.002)	(0.001)
Size	-0.163	-1.191	-0.163	-1.191	-0.220
	(1.662)	(0.833)	(0.272)	(0.948)	(0.276)
Leverage	0.268	-0.174	0.268	-0.174	0.290
	(2.754)	(2.314)	(0.305)	(0.394)	(0.270)
SGAslackAss	4.357***	3.282***	4.357	3.282*	4.387
	(1.530)	(1.016)	(3.135)	(1.757)	(3.092)
ROA	1.185	-0.502	1.185	-0.502	1.030
	(3.957)	(2.840)	(3.808)	(1.026)	(3.642)
Constant	0.614	6.817	1.596	6.817*	2.288
	(10.497)	(12.723)	(1.982)	(4.096)	(1.684)
Year Controls	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	No	Yes	No
Fixed Effects	Yes	No	Yes	No	Yes
Standard errors	Default	Default	Clustered by subindustry	Clustered by subindustry	Clustered by subindustry
Observations	3,121	3,121	3,121	3,121	3,121
R-squared	0.008		0.008		0.008
Number of firmid	643	643	643	643	643

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

Table 10 – Regression results for robustness checks on volatility measure

The table shows the results from the robustness test on the volatility measure, including estimations of Model 1, 2 and 3 using: OLS with fixed effects, year controls in column 14 and 16, and GLS with random effects, year controls, industry controls in column 15. All the estimations employ standard errors clustered by subindustry.

	(14)	(15)	(16)
	Model 1	Model 2	Model 3
VARIABLES	TobinQ	TobinQ	TobinQ
RDChange	0.114***	1.028*	-0.061**
	(0.024)	(0.571)	(0.026)
Size	-4.260***	-1.196*	-0.485
	(1.373)	(0.650)	(0.495)
RDChangexSize		-0.276*	
		(0.160)	
RDIntensity			0.238
			(0.210)
RDChangexRDInt			0.049*
			(0.024)
CapitalIntensity			-0.026
			(0.040)
NetProfitMargin			-0.001
			(0.001)
Leverage	0.032	1.236	-0.171
	(0.935)	(0.980)	(0.573)
SGAslackAss	2.571***	2.766***	5.672*
	(0.675)	(0.487)	(3.150)
ROA	-1.088	-1.546***	-1.335
	(2.017)	(0.409)	(2.785)
CAPEXonAssets	-4.438***	-6.517***	
	(1.072)	(2.386)	
Constant	23.552***	8.501**	4.545
	(7.194)	(3.816)	(2.794)
Year Controls	Yes	Yes	Yes
Industry Controls	No	Yes	No
Fixed Effects	Yes	No	Yes
Standard errors	Clustered by subindustry	Clustered by subindustry	Clustered by subindustry
Observations	4,082	4,082	2,926
R-squared	0.067		0.252
Number of firmid	849	849	618

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

Table 11 - Regression results for robustness checks on capital intensity measure

The table shows the results from the robustness test on the capital intensity measure, including estimations of Model 1 and 2 using: OLS with fixed effects, year controls in column 17, and GLS with random effects, year controls, industry controls in column 18. All the estimations employ standard errors clustered by subindustry.

	(17)	(18)
	Model 1	Model 2
VARIABLES	TobinQ	TobinQ
RDVolStd3	2.012**	6.337*
	(0.769)	(3.592)
Size	-3.744***	-1.821**
	(0.766)	(0.758)
RDVolStd3xSize		-0.822*
		(0.443)
CAPEXyes	-3.646	-2.950
	(2.941)	(1.906)
Leverage	-0.128	0.098
	(0.707)	(0.899)
SGAslackAss	2.281***	2.302***
	(0.244)	(0.245)
ROA	0.209	0.084
	(0.939)	(0.890)
Constant	23.189***	12.618**
	(5.694)	(5.251)
Year Controls	Yes	Yes
Industry Controls	No	Yes
Fixed Effects	Yes	No
Standard errors	Clustered by subindustry	Clustered by subindustry
Observations	4,346	4,346
R-squared	0.024	
Number of firmid	870	870

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

REFERENCE LIST

Aboody, D., & Lev, B. (2000). Information Asymmetry, R&D, and Insider Gains. *The Journal of Finance*, *55*(6), 2747–2766. https://doi.org/10.1111/0022-1082.00305

Akerlof, G. A. (1970). The Market for 'Lemons': Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500. https://doi.org/10.2307/1879431

Arora, A., Gambardella, A., Magazzini, L., & Pammolli, F. (2009). A Breath of Fresh Air? Firm Type, Scale, Scope, and Selection Effects in Drug Development. *Management Science*, *55*(10), 1638–1653. https://doi.org/10.1287/mnsc.1090.1055

Beckman, C. (2006). The Influence of Founding Team Company Affiliations on Firm Behavior. *Academy of Management Journal*, *49*. https://doi.org/10.5465/AMJ.2006.22083030

Bernstein, J. I., & Nadiri, M. I. (1989). Rates of Return on Physical and R&D Capital and Structure of the Production Process: Cross Section and Time Series Evidence. In B. Raj (Ed.), *Advances in Econometrics and Modelling* (pp. 169–187). Springer Netherlands. https://doi.org/10.1007/978-94-015-7819-6_12

Biopharmaceutical Research & Development: The Process Behind New Medicines (2015), Pharmaceutical Research and Manufacturers of America, http://phrma-docs.phrma.org/sites/default/files/pdf/rd_brochure_022307.pdf

Brown, J. R., & Petersen, B. C. (2011). Cash holdings and R&D smoothing. *Journal of Corporate Finance*, *17*(3), 694–709. https://doi.org/10.1016/j.jcorpfin.2010.01.003

Brush, T. H., Bromiley, P., & Hendrickx, M. (2000). The free cash flow hypothesis for sales growth and firm performance. *Strategic Management Journal*, *21*(4), 455–472. https://doi.org/10.1002/(SICI)1097-0266(200004)21:4<455::AID-SMJ83>3.0.CO;2-P

Center for Drug Evaluation and Research. (2019). FDA's Drug Review Process: Continued. *FDA*. https://www.fda.gov/drugs/information-consumers-and-patients-drugs/fdas-drug-review-process-continued

Center for Drug Evaluation and Research. (2022). Frequently Asked Questions on Patents and Exclusivity. *FDA*. https://www.fda.gov/drugs/development-approval-process-drugs/frequently-asked-questions-patents-and-exclusivity

Cheng, S. (2004). R&D Expenditures and CEO Compensation. *The Accounting Review*, *79*(2), 305–328. https://doi.org/10.2308/accr.2004.79.2.305

Cohen, W. M., & Klepper, S. (1992). The tradeoff between firm size and diversity in the pursuit of technological progress. *Small Business Economics*, *4*(1), 1–14. https://doi.org/10.1007/BF00402211

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, *35*(1), 128–152. https://doi.org/10.2307/2393553

Demirel, P., & Mazzucato, M. (2012). Innovation and Firm Growth: Is R&D Worth It? *Industry and Innovation*, *19*(1), 45–62. https://doi.org/10.1080/13662716.2012.649057

Duppati, G., Sune, A., & Samanta, N. (2017). Corporate governance, research and development volatility and firm performance—Evidence from Spain and Ireland. *Cogent Economics & Finance*, *5*(1). https://doi.org/10.1080/23322039.2017.1317117

Eisenhardt, K. M. (1989). Agency Theory: An Assessment and Review. *The Academy of Management Review*, *14*(1), 57–74. https://doi.org/10.2307/258191

Galindo-Rueda, F., & Verger, F. (2016). *OECD Taxonomy of Economic Activities Based on R&D Intensity*. OECD. https://doi.org/10.1787/5jlv73sqqp8r-en

Gopalakrishnan, S., & Bierly III, P. E. (2006). The impact of firm size and age on knowledge strategies during product development: A study of the drug delivery industry. *IEEE Transactions on Engineering Management*, *53*(1), 3–16. Scopus. https://doi.org/10.1109/TEM.2005.861807

Hai, B., Gao, Q., Yin, X., & Chen, J. (2019). R&D volatility and market value: The role of executive overconfidence. *Chinese Management Studies*, *14*(2), 411–431. https://doi.org/10.1108/CMS-05-2019-0170

Hall, B. H. (2002). The financing of research and development. *Oxford Review of Economic Policy*, *18*(1), 35–51. Scopus. https://doi.org/10.1093/oxrep/18.1.35

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

Hall, B. H., & Lerner, J. (2009). *The Financing of R&D and Innovation* (Working Paper No. 15325). National Bureau of Economic Research. https://doi.org/10.3386/w15325

Hickey, K. J. (2020). Patent law: A handbook for Congress. *CRS Reports (Library of Congress. Congressional Research Service)*.

Hottenrott, H., Hall, B. H., & Czarnitzki, D. (2016). Patents as quality signals? The implications for financing constraints on R&D. *Economics of Innovation and New Technology*, *25*(3), 197–217. https://doi.org/10.1080/10438599.2015.1076200

Jensen, M. C. (1993). The Modern Industrial Revolution, Exit, and the Failure of Internal Control Systems. *The Journal of Finance*, *48*(3), 831–880. https://doi.org/10.1111/j.1540-6261.1993.tb04022.x

Jensen, M. C., & Meckling, W. H. (1976). *Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure* (SSRN Scholarly Paper No. 94043). https://doi.org/10.2139/ssrn.94043

Jeny, A., & Moldovan, R. (2020). *Accounting for Intangible Assets—Insights from Meta-Analysis of R&D Research* (SSRN Scholarly Paper No. 3120397). https://doi.org/10.2139/ssrn.3120397

Jiang, C., John, K., & Larsen, D. (2021). R&D investment intensity and jump volatility of stock price. *Review of Quantitative Finance and Accounting*, *57*(1), 235–277. https://doi.org/10.1007/s11156-020-00944-3

Kang, T., Baek, C., & Lee, J.-D. (2017). The persistency and volatility of the firm R&D investment: Revisited from the perspective of technological capability. *Research Policy*, *46*(9), 1570–1579. https://doi.org/10.1016/j.respol.2017.07.006

Lang, L., Ofek, E., & Stulz, RenéM. (1996). Leverage, investment, and firm growth. *Journal of Financial Economics*, *40*(1), 3–29. https://doi.org/10.1016/0304-405X(95)00842-3

Li, D. (2011). Financial Constraints, R&D Investment, and Stock Returns. *The Review of Financial Studies*, *24*(9), 2974–3007. https://doi.org/10.1093/rfs/hhr043

Long, C. (2002). Patent Signals. *The University of Chicago Law Review*, *69*(2), 625–679. https://doi.org/10.2307/1600501

Lubatkin, M. H., Simsek, Z., Ling, Y., & Veiga, J. F. (2006). Ambidexterity and Performance in Small-to Medium-Sized Firms: The Pivotal Role of Top Management Team Behavioral Integration. *Journal of Management*, *32*(5), 646–672. https://doi.org/10.1177/0149206306290712

Máñez, J. A., Rochina-Barrachina, M. E., Sanchis, A., & Sanchis, J. A. (2009). The role of sunk costs in the decision to invest in r & d. *Journal of Industrial Economics*, *57*(4), 712–735. Scopus. https://doi.org/10.1111/j.1467-6451.2009.00398.x

Marilena Mironiuc, Maria Carmen Huian, Alina Țaran, & Mihaela Curea. (2022). Financial market reaction to R&D volatility in the pharmaceutical industry. A multi-country study. *Journal of Business Economics and Management*, *23*(5). https://doi.org/10.3846/jbem.2022.17844

Mazzucato, M., & Tancioni, M. (2012). R&D, patents and stock return volatility. *Journal of Evolutionary Economics*, *22*(4), 811–832. https://doi.org/10.1007/s00191-012-0289-x

Mudambi, R., & Swift, T. (2011). Proactive R&D management and firm growth: A punctuated equilibrium model. *Research Policy*, *40*(3), 429–440. https://doi.org/10.1016/j.respol.2010.10.014

Mudambi, R., & Swift, T. (2014). Knowing when to leap: Transitioning between exploitative and explorative R&D. *Strategic Management Journal*, *35*(1), 126–145. https://doi.org/10.1002/smj.2097

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, *5*(2), 147–175. https://doi.org/10.1016/0304-405X(77)90015-0

Nason, R. S., & Patel, P. C. (2016). Is cash king? Market performance and cash during a recession. *Journal of Business Research*, *69*(10), 4242–4248. https://doi.org/10.1016/j.jbusres.2016.03.001

Patel, P. C., Guedes, M. J., Soares, N., & da Conceição Gonçalves, V. (2018). Strength of the association between R&D volatility and firm growth: The roles of corporate governance and tangible asset volatility. *Journal of Business Research*, *88*, 282–288. https://doi.org/10.1016/j.jbusres.2017.12.033

Pennetier, C., Girotra, K., & Mihm, J. (2018). *R&D Spending: Dynamic or Persistent?* (SSRN Scholarly Paper No. 2671828). https://doi.org/10.2139/ssrn.2671828

Reinganum, J. F. (1983). Uncertain Innovation and the Persistence of Monopoly. *The American Economic Review*, *73*(4), 741–748.

Congressional Budget Office (2021, April). *Research and Development in the Pharmaceutical Industry*. https://www.cbo.gov/publication/57126

Spence, A. (2002). Signaling in Retrospect and the Informational Structure of Markets. *American Economic Review*, *92*, 434–459. https://doi.org/10.1257/00028280260136200

Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, *87*(3), 355–374. https://doi.org/10.2307/1882010

Tong, J., & Zhang, F. (2014a). *Do Capital Markets Punish Managerial Myopia? Evidence from Myopic R&D Cuts* (SSRN Scholarly Paper No. 2395774). https://doi.org/10.2139/ssrn.2395774

Tong, J., & Zhang, F. (2014b). More Evidence That Corporate R&D Investment (and Effective Boards) Can Increase Firm Value. *Journal of Applied Corporate Finance*, *26*(2), 94–100. https://doi.org/10.1111/jacf.12071

U.S. total medicine spending 2002-2021. (n.d.). Statista. Retrieved 17 May 2023, from https://www.statista.com/statistics/238689/us-total-expenditure-on-medicine/

Walter, J. (2012). The Influence of Firm and Industry Characteristics on Returns from Technology Licensing Deals: Evidence from the US Computer and Pharmaceutical Sectors. *R& D Management*, *42*. https://doi.org/10.1111/j.1467-9310.2012.00693.x

Wang, Y., Du, R., Koong, K. S., & Fan, W. (2017). Effects of R&D policy choice on accounting performance and market value. *R&D Management*, *47*(4), 545–556. https://doi.org/10.1111/radm.12225

Wong, C. H., Siah, K. W., & Lo, A. W. (2019). Estimation of clinical trial success rates and related parameters. *Biostatistics*, *20*(2), 273–286. https://doi.org/10.1093/biostatistics/kxx069

Wooldridge, J. M. (2018). *Introductory econometrics: A modern approach* (Ekonomihögskolans bibliotek Kursbok Q Wooldridge; Seventh edition.). Cengage.

Xiang, E., Gasbarro, D., Cullen, G., & Ruan, W. (2020). Does R&D expenditure volatility affect stock return? *Journal of Contemporary Accounting & Economics*, *16*(3). https://doi.org/10.1016/j.jcae.2020.100211