MASTER THESIS

R&D investments and stock return volatility

A study on the biotechnological and pharmaceutical industry in Europe

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Abstract

This study investigates the relationship between R&D investment intensity and stock return volatility in the European pharmaceutical and biotechnological industry. Using panel data, the analysis explores the impact of R&D investments on both total stock return volatility and idiosyncratic volatility. The sample comprises 206 publicly listed pharmaceutical and biotechnological firms from 2015 to 2021, with a specific focus on R&D investments related to COVID-19 during the years 2020 and 2021. The results demonstrate no significant relationship between R&D investment intensity and idiosyncratic risk. In contrast, a negative association is observed between R&D investment intensity and total stock return volatility. However, it is noted that firms with higher R&D investment intensity experienced increased volatility in their total stock returns specifically during the COVID-19 pandemic. The results of this study suggest that pharmaceutical and biotechnological firms can potentially decrease the level of volatility in their stock returns by investing in R&D activities.

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1. Introduction

Investing in research and development (R&D) is becoming increasingly important to stock market participants because of its impact on investors' portfolio risks and expected returns. Many firms invest in R&D and innovation because it is seen as a critical strategic asset for gaining a competitive advantage and improving their market performance. In addition, investing in R&D is considered essential for firms to maintain a strong market position and economic wellbeing (Ehie & Olibe, 2010). However, investing in R&D is considered risky because R&D investments involve a long process with a high degree of uncertainty surrounding a firm's future profits due to a lack of understanding of how the investments will turn out (Chan et al., 2001; Holmstrom, 1989). Despite the fact that investing in R&D does not guarantee any future benefits or attractive stock returns for investors, firms still need to spend heavily on R&D activities. This is because a firm needs to keep up with advancements and trends to create new products or services to differentiate themselves and gain a competitive advantage in these competitive environments. This increased importance of R&D investment raises the question of how these investments affect a firm's stock performance, such as stock return volatility.

Typically, a firm's total stock return volatility determines the risk level associated with investing in the firm's stock. Total stock return volatility can be divided into two components: systematic volatility and idiosyncratic volatility. Systematic volatility is the risk associated with the overall market, while idiosyncratic is the risk associated with a particular stock or firm. A significant amount of literature has studied the risk associated with R&D investments and found that firms with higher R&D spending are more risky than those without. Gharbi et al. (2014) investigated the relationship between R&D investments and the stock return volatility of high-tech French firms and suggested that R&D intensity may be a contributing factor to the stock return volatility.

Additionally, Xu (2006) explored how the R&D strategies chosen by US biotech firms affect their share price volatility. Mazzucato and Tancioni (2012) also examined whether firms in the pharmaceutical industry that invest heavily in innovation experience high volatility in their returns. Their findings suggest that there is a positive and significant correlation between R&D intensity, idiosyncratic volatility, and various patent-related metrics. Additionally, Zhang (2015) investigated R&D expenditure in the context of financial distress and discovered a positive correlation between R&D investments and financial distress risk.

Furthermore, investments in intangible assets like R&D can often create information asymmetry. This is because corporate managers can constantly monitor changes in investment products for individual assets, but outsiders can only access highly summarized information when it is made public (Aboody & Lev, 2000). As a result, R&D investments can contribute to information asymmetry. Studies have shown that information asymmetry is more pronounced for firms that invest in R&D. This is because R&D investments have several unique characteristics. One of these is that R&D-intensive firms often have little incentive to disclose information about their projects. This is because keeping their innovations secret can help protect them from being copied and maintain their competitive advantage.

Additionally, R&D investments are exclusive to the firms that carry them out, making it difficult for investors to gain insight into the productivity and value of a particular firm's R&D. This leads to information asymmetry regarding the firms' prospects and growth potentials, which is largely attributed to R&D investments. Moreover, Gu et al. (2005) found that the level of information asymmetry in high-tech R&D-intensive firms is high due to the complexity and technical nature of innovation. Furthermore, accounting rules often treat R&D investments differently from other types of investments. In some cases, R&D investments are expensed immediately in financial statements, which means that investors do not receive any information on changes in the value or productivity of R&D investments. This can make it difficult for investors to accurately assess the potential risks and rewards of investing in R&D.

This study aims to contribute to the existing body of literature by exploring the correlation between R&D investment and stock return volatility in the context of European countries in the biotechnology and pharmaceutical industry. While most prior studies have focused on the United States, which is the world leader in R&D investments, equivalent studies in European settings are limited. Hence, this study aims to fill this gap and provide insights into the impact of R&D investment on the European stock market. According to the 2022 Fortune Global 500, four of the top 10 pharma firms by revenue are European[1]. Additionally, this study is relevant due to the accounting and structural distinctions between the United States and Europe. US firms use the GAAP accounting methods to report R&D costs, while most European firms employ the IAS-IFRS accounting rules, which treat R&D costs differently. Furthermore, since 2000, global spending on R&D has increased threefold, from $675 billion to $2.4 trillion

[1] The world's 10 biggest pharmaceutical companies raked in over $700 billion in revenue in 2021. https://fortune.com/2022/08/15/global-500-biggest-pharma-companies/

in 2020[2]. It is clear that R&D investments have become a major factor in innovation and economic growth. Therefore, this research proposes R&D investment as a potential factor influencing stock return volatility.

Moreover, this study will investigate the hypothesis that stock return volatility increases with R&D investment intensity and is higher during the COVID-19 pandemic. The COVID-19 pandemic has been classified as a global health crisis with radical economic repercussions. It has placed immense pressure on the biotechnology and pharmaceutical industries to invest heavily in R&D to quickly develop and produce effective and safe COVID-19 vaccines and drugs. These investments can lead to higher future cash flows, which can result in more stable returns for investors. However, rapid R&D investments in a brief period of time can be risky and may take several years to yield results, and investors may be impatient or require short-term returns. In such cases, R&D investments may lead to higher stock return volatility and lower returns in the short term. Liu et al. (2020) studied the effect of the COVID-19 outbreak on countries whose stock markets were most affected and discovered that the pandemic has caused investors to lose confidence in the stock market due to the high level of uncertainty. Additionally, Baker et al. (2020) identified the COVID-19 pandemic as having the most significant impact on stock market volatility in the history of pandemics.

Furthermore, this study focuses on the biotechnology and pharmaceutical firms listed on the European Stock Exchange, active from 2015 to 2021. The analysis is valuable because the pharmaceutical and biotechnology industry is a vital asset to the European economy. The European Federation of Pharmaceutical Industries and Associations (EFPIA) report highlights that the pharmaceutical and biotechnology sector amounts to 18.9 percent of total business R&D expenditure worldwide (EFPIA, 2019). In 2018, the pharmaceutical and biotechnology sector invested more than € 35,300 million in R&D in Europe. Additionally, during the frame 2020 and 2021; we can distinguish the R&D investments for COVID-19. Furthermore, examining the relationship between R&D investment intensity and stock return volatility in the pharmaceutical and biotech industries during the pandemic provides valuable insights into the resilience and performance of firms facing unprecedented challenges. Firms that allocate higher investments in R&D demonstrate a stronger commitment to innovation and potential for future growth. By analyzing this relationship, investors can identify firms that effectively manage

[2] Congressional Research Service (CRS). Global Research and Development Expenditures: Fact Sheet. https://sgp.fas.org/crs/misc/R44283.pdf

market volatility through R&D investments, indicating their potential for creating long-term value. This information helps investors in identifying investment opportunities aligned with their long-term goals, enhancing their understanding, improving decision-making, and effectively managing risks.

The present research addresses the following research questions:

- *Do firms in the biotech and pharmaceutical industry with higher R&D investment experience higher total return volatility, and is the impact stronger during the COVID-19 pandemic?*

- *Do firms in the biotech and pharmaceutical industry with higher R&D investment experience higher idiosyncratic volatility, and is the impact stronger during the COVID-19 pandemic?*

Following Gharbi et al. (2014) and Hamim et al.'s (2020) approach, which studied whether stock volatility is positively associated with R&D investments, this study utilizes panel data regression analysis. The panel data regressions are used to determine whether the independent variable (R&D-intensity) affects the dependent variable (volatility).

The results of this study reveal a negative association between R&D investment intensity and total stock return volatility, thus rejecting hypothesis 1. This finding contradicts the findings of previous studies conducted by Xu (2006), Mazzucato and Tancioni (2012), and Gharbi et al. (2014). However, it is interesting to note that firms with higher R&D investment intensity experienced increased volatility in their total stock returns specifically during the COVID-19 pandemic, supporting hypothesis 1a. Furthermore, no significant relationship is found between R&D investment intensity and idiosyncratic volatility, leading to the rejection of hypothesis 2 in this study. This finding is inconsistent with prior research conducted by Gharbi et al. (2014). Additionally, hypothesis 2a, which proposes that firms with higher R&D investment intensity experience higher idiosyncratic volatility during the COVID-19 pandemic, is not supported. In summary, the results indicate that pharmaceutical and biotechnological firms have the potential to decrease the level of volatility in their stock returns by investing in R&D activities.

The remainder of this paper is organized as follows. Section 2 presents the literature review and discusses the theoretical background of the research. The hypotheses development is discussed in section 3. Lastly, section 4 discusses the data and methodology of the study.

2. Literature Review

2.1 Theoretical background: R&D Investment

The current global competition encourages firms to invest in R&D and innovations as it is considered a critical strategic asset for obtaining a competitive advantage and improving firms' market performance. Moreover, R&D is also considered an essential element in attaining and sustaining a solid market position and economic well-being for firms (Ehie & Olibe, 2010). However, typically, R&D investments are not performed with the expectation to yield immediate profit but rather to conduce to the long-term profitability of a firm. R&D investments involve a lengthy process with a great degree of uncertainty surrounding a firm's future profit because of no clear understanding of how R&D investments will turn out (Chan et al., 2001; Holmstrom, 1989).

Despite the fact that investing in R&D may not guarantee any future benefits or attractive stock returns, firms must continue to invest heavily in R&D projects. This is because staying up-to-date with advancements and trends is essential for firms to create new products or services that will give them an edge over their competitors in the competitive market. For example, for tech firms, there is a constant need to invest in R&D, as returns for firms in this industry are primarily dependent on capturing the latest technological advancements in their product lines. Driver & Guedes (2012) point out that R&D has certain characteristics: the assets are intangible, making them primarily sunk or irreversible; it is hard to reap the full benefits of R&D unless there is protection through patents, secrecy, or unique complementary assets; and the cash flows are both long-term and risky.

Furthermore, according to the ***Behavioral Theory of Firm*** (BTOF) proposed by Cyert & March (1963), the level of R&D investment or R&D intensity can be explained by the idea that firms compare their current performance to predetermined aspiration levels. If performance falls below the aspiration level, problemistic search is initiated, which is a search that is motivated by a problem and is aimed at finding a solution (Greve, 2003). The general prediction is that problemistic search is associated with increased organizational risk-taking or change. Moreover, The BTOF model was found to be robust across many empirical studies across contexts and different strategic outcomes, such as new product introduction, innovation, and R&D investments. For instance, Chen et al., (2007) studied the situational and institutional determinants of R&D intensity of publicly traded manufacturing U.S. companies and found that

R&D intensity increases as performance falls below aspirations. Their findings are comparable to Greve (2003), who found that performance below a firm's aspiration level encourages problemistic search through R&D and that firms launch innovations in response to low performance. So, in sum, the worse firm performance gets, the greater the likelihood that the management of firms will engage in risk-taking to regain the firm's competitive advantage.

However, the level of risk-taking effect is likely to depend on the attributes of the firm's top executives. Hambrick and Mason (1984) wrote a paper that gives us a central understanding of where firms can derive competitive advantage based on the upper echelon. The ***Upper Echelon Theory*** proposes that the characteristics and traits of top executives, such as their education, experience, and cognitive ability, can have a significant impact on a firm's performance and decision-making. This theory may be relevant to the relationship between R&D and stock return volatility in several ways. First, the upper echelon theory suggests that the characteristics of top executives can affect a firm's R&D investments. Second, the upper echelon theory suggests that the characteristics of top executives can affect the way a firm manages and reports on its R&D investments. For example, executives with strong communication skills and a deep understanding of the firm's R&D projects may be better able to clearly explain the value and potential benefits of R&D investments to investors and other stakeholders, leading to more positive perceptions and lower stock return volatility. So, the upper echelon theory may provide some insight into how the characteristics and traits of top executives can affect a firm's R&D investments and stock return volatility.

Many studies have shown that CEOs' personalities can significantly influence decision-making within a firm. For example, Gow et. al. (2016) used linguistic features of CEOs' speeches during conference calls to measure their Big Five personality traits. They found that the personality traits of a CEO are significantly related to financing choices of firm performances. Other scholars have shown that CEO attributes influence R&D spending (Barker & Mueller, 2002). One attribute that has received considerable attention from scholars is ***CEO overconfidence***. CEO overconfidence refers to a situation in which a CEO has an excessively positive view of their own abilities and the prospects of the firm, leading them to make decisions that are overly optimistic and not well-supported by evidence. The CEO overconfidence theory is supported by empirical evidence, which suggests that CEO overconfidence is positively correlated with poor investment behavior, such as negative firm performance and value-decreasing acquisitions (Kim & Park, 2020; Malmendier & Tate, 2005). Nonetheless, Zulfiqar

et al. (2021) conducted research to determine the influence of CEOs' psychological traits of overconfidence on R&D investment. The results showed that firms with overconfident CEOs had a higher stock return volatility.

Moreover, the ***Signaling Theory*** states that firms have reasons to communicate (or signal) the capital market to reduce information asymmetry between managers and outsiders since firms that experience high information asymmetry are more liable to be undervalued (Ang & Cheng, 2011). In the context of R&D investments, signaling theory suggests that firms that invest in R&D are sending a signal to the market about their confidence in their future prospects and growth potential. This signal can influence the stock price and overall return on investment. For example, if a firm is perceived as being innovative and forward-thinking, investors may be more likely to buy its stock, which can drive up the price and increase the return on investment. On the other hand, if a firm is seen as being stagnant and unwilling to invest in R&D, investors may be less likely to buy its stock, which can cause the price to drop and decrease the return on investment. Using event study methodology, Chan et al. (1990) studied the stock-price response to announcements of R&D investments of 95 US firms between 1979 and 1985. They found that the stock market responded positively through abnormal returns and that the response is positive even for firms that also experience an earnings decline. In addition, Kim et al. (2020) researched how R&D investments affected stock market returns in South Korea and found that investment in R&D is an excellent signaling strategy to mitigate information asymmetry issues and improve firm value.

Lastly, another theory that can be used to explain the impact of R&D on stock prices and volatility is the ***resource-based view (RBV)***. The RBV is a theory in strategic management that argues that the resources and capabilities of a firm are the key determinants of its competitive advantage and performance (Barney, 2000). The RBV posits that a firm's resources and capabilities are valuable, rare, inimitable, and non-substitutable and that these characteristics enable the firm to create and sustain a competitive advantage.

In the context of R&D and stock return volatility, the RBV can be used to explain the impact of R&D on stock prices and volatility. R&D can be considered a key resource and capability for firms that engage in innovation and technological development. R&D involves a significant level of investment in the development of new products, technologies, or processes, which can be seen as a valuable and rare resource for firms. If a firm's R&D efforts are successful, they may be able to create and sustain a competitive advantage through the

development of new products or technologies that are inimitable and non-substitutable. This can lead to higher stock prices and potentially lower volatility in stock returns, as investors may perceive the firm as having a strong commitment to innovation and long-term growth.

On the other hand, R&D can also be a source of uncertainty and risk, which can affect the potential returns and volatility of a firm's stock. Firms that invest heavily in R&D may be more likely to experience unexpected outcomes, such as technological failure or market disruption, which can cause their stock prices to fluctuate more. This can increase the volatility of their stock returns and potentially affect the sustainability of their competitive advantage. So, in short, the RBV can be used to explain the impact of R&D on stock return volatility by highlighting the role of R&D as a valuable and rare resource that can enable firms to create and sustain a competitive advantage but can also be a source of risk and uncertainty that can affect stock prices and volatility.

2.2 R&D investment risks

2.2.2 Information Asymmetry

When firms invest in R&D, the managers of those firms may have access to more detailed information about the productivity of their investments than outsiders do. This can create a situation where outsiders only have access to highly summarized information at certain times when it is publicly released. This is known as information asymmetry (Aboody & Lev, 2000). Research has demonstrated that firms with R&D expenditures have a higher degree of information asymmetry than those without. This is due to the fact that R&D investments have distinct qualities that set them apart from other investments First, firms that heavily invest in R&D have little incentive to reveal information about their projects, as secrecy is seen as an effective way to protect innovation from being copied and to maintain a competitive edge. For instance, Cohen et al. (2000) studied a dataset of 1,478 US manufacturing laboratories and discovered that the choice to keep inventions confidential was preferred over patenting to safeguard innovation. Furthermore, Bhushan's (1989) study demonstrates that a positive association exists between firm size and the number of financial analysts who follow them. This finding indicates that smaller firms may have less financial analyst coverage, leading to a higher level of information asymmetry in comparison to larger firms. Thus, larger firms have a greater analyst following and, consequently, more private information available to investors.

Additionally, R&D investments are exclusive to the firms that carry out the projects, making it difficult for investors to gain insight into the productivity and worth of a particular firm's R&D (Aboody & Lev, 2000). Consequently, R&D investment is responsible for creating asymmetry in the transmission of information about the firms' prospects and growth potentials. Gu et al. (2005) found that this is especially true for tech-focused firms due to the complexity and technical nature of their innovations.

Moreover, accounting and reporting rules treat R&D investments differently from other investments. These rules require that financial investments be reported quarterly and annually and that the value of tangible assets is regularly assessed. This provides investors with current information about changes in asset values. However, this is not the case with R&D; R&D investments are, in general, immediately expensed in financial statements and more rarely capitalized depending on the accounting standards used by each firm and country. Under the United States Generally Accepted Accounting Principles (GAAP), R&D investments must be expensed as costs in the period in which they are incurred. This means that the costs of R&D are recognized immediately, which can have a more significant impact on the firm's reported profitability. This can make the financial performance of the firm more volatile, which can lead to increased volatility in the stock return.

On the other hand, under the International Financial Reporting Standards (IFRS) and International Accounting Standards (IAS) rules, research costs are treated as an expense yearly, just as GAAP[3]. However, one benefit of the IFRS and IAS rules when dealing with R&D investments is that they allow some development costs to be capitalized. This means that these costs can become assets on the firm's balance sheet rather than being recorded as expenses. This provides investors with more information about the value and productivity of the firm's R&D investments. In contrast, under the GAAP, no information about the value and productivity of R&D investments is reported or available to investors. This can make it more difficult for investors to assess the quality of the firm's R&D investments and make informed decisions about whether to buy its stock. So, overall, the treatment of R&D investment under IFRS or IAS can potentially lower stock return volatility compared to GAAP, as it allows for the costs of R&D to be recognized over time rather than all at once. This can make the firm's financial performance more predictable and consistent, which can reduce the volatility of its stock return.

[3] According to International Accounting Standards (IAS38), research expenditures should be expensed when they are incurred, and development expenditures can be capitalized if certain criteria are met. One such criterion is whether it is probable that the expected future economic benefits will flow to the entity or not.

2.2.1 Financial Distress

Like all investments, R&D investments contribute to certain risks. Financial distress refers to a situation in which a firm is unable to meet its financial obligations or is at risk of bankruptcy. R&D investments are often seen as a potential source of financial distress, as they can involve significant upfront costs and a high degree of uncertainty surrounding future returns. Investments in R&D can lead to increased financial distress if they do not generate sufficient returns. If a firm invests heavily in R&D and the projects do not provide a sufficient return on investment, this can put financial strain on the firm and increase the risk of financial distress. This, in turn, can lead to increased stock return volatility, as investors may become concerned about the firm's financial stability and ability to generate future profits.

Moreover, financial distress can affect a firm's ability to invest in R&D. If a firm is experiencing financial distress, it may be forced to cut back on R&D spending in order to conserve cash and reduce expenses. This can reduce the firm's ability to innovate and develop new products and services, potentially hindering its long-term growth and leading to increased stock return volatility (Zhang, 2015). In addition, Zhang's study showed that there is a positive and significant relationship between R&D investments and financial distress risk. The findings suggest that this effect is more significant for financially constrained firms. This is because R&D investments are risky investments that utilize substantial resources. As for unconstrained firms, failure of R&D projects should not induce existential risks since these firms have easy access to external funds. Conversely, financially constrained firms do not have sufficient resources to absorb failing R&D projects.

2.3 Stock return volatility

Stock market returns are the earnings acquired upon investing in the stock market. Stock volatility represents the degree of price movements of stock returns of a security over a specific period. If the prices of a stock change rapidly in a short period, it is said to have high volatility. Contrarily, if a stock price does not vary too quickly over time, it is said to have low volatility. Stock volatility is a commonly used measure of risk, measured as the standard deviation of returns over a particular period (Chan et al., 2001; Gharbi et al., 2014). A greater standard deviation implies a greater spread of stock returns, and the investment in that security becomes riskier. So, high volatility generally makes an investment riskier, thus increasing the risk of loss for investors.

2.3.1. Types of volatility

Total stock volatility consists of two components: systematic volatility and idiosyncratic volatility. Systematic volatility, also known as "market risk," is the risk caused by external factors to the firm and affects the entire market, not just a particular stock or industry. This type of volatility is beyond the control of investors and is typically caused by factors that affect the economy as a whole, such as changes in interest rates, inflation, and economic growth. Adrian et al. (2008) argue that overall market volatility is priced and related to macroeconomic risk (business cycle risk). Beta is considered a useful statistical tool to measure a stock's volatility compared to the entire market. Based on the beta analysis, the entire market has a beta of 1. When the beta of a single stock is less than 1, this implies a stock is less volatile than the market. The opposite holds when the beta is greater than 1, implying the stock would be more volatile than the market.

On the other hand, idiosyncratic volatility, commonly known as firm-specific risk, is the risk inherent to a particular to a specific firm or industry, making it more difficult to predict and manage. A significant amount of the variation in the volatility of an individual stock over time can be attributed to idiosyncratic volatility, according to studies by Ferreira et al. (2007) and Goyal et al. (2003).

Models such as the CAPM and Fama-French Three-Factor model assume that investors can eliminate idiosyncratic volatility through diversification. However, circumstances exist in which investors do not hold a well-diversified portfolio, e.g., due to deficient information (Merton, 1987). Idiosyncratic volatility is therefore not eliminated. Campbell et al. (2001) estimated that investors should hold as many as 50 stocks to achieve adequate diversification. So, for undiversified investors, idiosyncratic volatility matters - investors should rely on market risk and incorporate the total risk in their decisions. Furthermore, the literature on idiosyncratic volatility is relatively scarce, perhaps due to the perception that it can be eliminated through diversification. However, there is evidence of research examining the relation between idiosyncratic volatility and expected return. For example, Research by Fu (2009) has shown that there is a strong and positive relationship between idiosyncratic volatility and the level of expected returns. Similarly, Goyal and Santa-Clara (2003) found that idiosyncratic volatility has a positive and significant impact on future stock market returns, indicating that it is an important factor to consider when making investment decisions.

2.3.2. Stock volatility and information asymmetry

Theoretical models suggest that when there is a higher degree of information asymmetry, stock return volatility is likely to increase. For example, French and Roll (1986) found that the level of stock return volatility is closely related to the quality and quantity of information that is available to investors. When investors have access to more and better information, stock return volatility tends to be lower. Levi et al. (2011) also found a positive relationship between information asymmetry and expected returns, while Attanasio (1990) argued that when information is scarce, stock prices are more volatile than they would be in a market where all investors have complete information.

2.3.3. Stock volatility and COVID-19

On March 11, 2020, the World Health Organization (WHO) declared the novel coronavirus, also known as COVID-19, a pandemic. This has had a wide-ranging impact on social, psychological, and economic systems. At the same time, the pandemic has also led to increased volatility in stock prices and returns. The uncertainty and disruption caused by COVID-19 has caused market fluctuations and increased investor risk aversion, leading to higher levels of stock return volatility. Several researchers have looked into the effect of the pandemic on financial market volatility. For instance, Ashraf (2020) observed a decline in the stock market growth rate due to increased confirmed COVID-affected cases using daily stock market data from January 22, 2020, to April 17, 2020. Moreover, Baek et al. (2020) conducted an industry-level analysis on the impact of COVID-19 on U.S. stock market volatility. The study found that certain economic indicators are major determinants of volatility, and that negative news about COVID-19 has a greater impact on stock market volatility than positive news. This suggests that there may be a negativity bias at play.

Furthermore, Baker et al. (2020) identify the COVID-19 pandemic as having the most significant impact on stock market volatility in the history of pandemics. Bora et al. (2021) conducted a study using daily data to examine how the Indian stock market was affected by the COVID-19 pandemic. They found that the market was much more volatile during the period after the outbreak than it was before. Moreover, Liu et al. (2020) observed that because of such an outbreak of COVID-19, the stock market of Asian countries was affected negatively, mainly in comparison to the other selected stock markets. The authors also found that the pandemic

has decreased investors' confidence levels in the stock market due to very high market uncertainty.

Moreover, the COVID-19 pandemic demanded that pharmaceutical and biotechnology firms invest heavily in R&D in a short time to discover and develop a possible vaccine. Heavy investment in R&D in a short period of time may be associated with sunk costs, which are costs that have already been incurred and cannot be recovered. These costs are typically not taken into consideration when making decisions about future investments, as they have already been incurred and cannot be changed. However, in the case of R&D investment, sunk costs may be relevant because they can represent a significant portion of the total investment in R&D. If a firm fails to succeed in its R&D efforts, there may be a large sunk cost. On the other hand, if the firm is successful, there may be a significant profit. This can result in increased volatility in the firm's stock price, as investors may be uncertain about the potential risks and rewards associated with the firm's ability to develop a successful product or technology.

2.4 Empirical evidence in biotech and pharma industry

2.4.1 Volatility of biotech and pharma industry

Both the biotech and pharmaceutical industries are considered to be high-tech and R&D-intensive. Previous research has shown that high-tech firms tend to be more volatile than low-tech firms. Gharbi et al. (2014) found a positive and significant relationship between stock volatility and R&D investment intensity in French high-tech firms. This suggests that the biotech and pharmaceutical industries, as high-tech and R&D-intensive industries, may be subject to higher levels of stock return volatility.

Xu (2006) studied how the R&D strategies of US biotech firms affect their share price volatility. He used portfolio analysis to analyze the relationship between drug discovery and development diversification and share price volatility and found that firms with diversified drug portfolios tend to have lower share price volatility and lower stock returns, while firms with more concentrated drug portfolios tend to have higher share price volatility and higher stock returns.

Moreover, Pérez-Rodríguez et al. (2012) investigated whether unexpected R&D news leads to large fluctuations and overreaction in the stock of pharmaceutical firms, using data from 1989 to 2008. They found no evidence of market overreaction. Later, Mazzucato and

Tancioni (2012) looked at whether firms in the pharmaceutical industry that invest heavily in innovation, through high levels of R&D and a large number of patents, experience high volatility in their returns. Their findings indicate that there is a positive and significant relationship between R&D intensity, idiosyncratic volatility, and several measures related to patents. This suggests that the level of innovation in a pharmaceutical firms can have an impact on its stock return volatility.

2.4.2 R&D activities in the biotech and pharma industry

The biotech and pharmaceutical industries are closely related, as the biotech industry focuses on developing new drugs and technologies using biological processes, while the pharmaceutical industry is primarily concerned with producing and distributing those drugs. R&D in the pharmaceutical and biotechnology industries is considered to be more risky compared to other high-tech industries because the process of discovering and developing drugs is long, expensive, and full of uncertainty in terms of how the human body will respond to drugs. It typically takes between 10 and 20 years from the initial concept to when a product is launched. Out of every 10,000 substances created in labs, only one to two will successfully pass all the necessary stages to become a marketable medicine[4] (Lerner et al., 2003). Research by DiMasi et al. (2007) found that the average cost of getting a single product approved and launched was approximately $1,318 million.

However, during the COVID-19 pandemic, this process operated differently. By the end of 2020, three COVID-19 vaccines were granted emergency-use authorization (EUA) or other forms of approval in Europe, the United Kingdom, or the United States. Only eleven months after the COVID-19 sequence was published, which is considered a highly unusual development timeline for the biotech and pharma industry. Several factors related to the global humanitarian crisis made it possible to develop a working vaccine in such a short period. For example, regulatory applications for COVID-19 vaccine candidates were processed much faster than usual, taking just a week instead of the typical 30 days. In addition, clinical development phases were initiated before previous phases were finished. Furthermore, important information about COVID-19 was rapidly shared with the entire scientific community (Agrawal et al.,

[4] European Federation of Pharmaceutical Industries and Associations. The Pharmaceutical Industry in Figures 2019. https://www.efpia.eu/publications/downloads/efpia/the-pharmaceutical-industry-in-figures

2021). As a result, R&D related to the development of the COVID-19 vaccine did not face any issues with information asymmetry.

2.4.3 Asymmetric information in biotech and pharma industry

Information asymmetry varies across different industries. It has been found to be particularly prevalent in R&D intensive industries, such as the high-tech sector and the biotechnology and pharmaceutical industry (Hall, 2002; Lerner et al., 2003). This is because R&D investments in this industry are typically highly complex and technical, and the results of R&D activities can be difficult to predict. As a result, the managers of biotech and pharma firms often have more detailed and up-to-date information about the firm's R&D projects than external investors and stakeholders.

Additionally, R&D projects in this industry are often unique to the firms that carry them out, making it difficult for investors to gain insight into the productivity and value of a firm's R&D investments. These factors can make it challenging for investors to accurately assess the potential value of R&D investments in the biotech and pharmaceutical industry. As a result, investors often rely on other types of non-financial information released by firms to determine the value of R&D investments. In the biotech and pharma industry, the progress of a drug in its clinical trials is seen as a good sign that the firm is generating value (Amir & Lev, 1996; McConomy & Xu, 2004). However, much of the released information is highly uncertain due to the low success rate of drug discovery and development (Xu, 2011). For example, a successful phase I trial does not guarantee success in phase II. As a result, it can be difficult for investors to assess how a firm is progressing.

3. Hypotheses development

R&D expenditures generate information asymmetry related to firms' prospects and growth potential. Since stock return volatility increases when the degree of information asymmetry rises, it is anticipated that stock return volatility will increase with R&D expenditures. The study makes a distinction between total stock volatility and idiosyncratic volatility. In addition, since pharmaceutical and biotechnology firms invested heavily in R&D in a short time during the pandemic, this study develops two sub-hypotheses to determine whether volatility shows notable differences between the pre-COVID-19 and COVID-19 pandemic periods.

The study develops it's first and sub-hypothesis:

H1: *Firms in the biotech and pharmaceutical industry with higher R&D investment intensity experience higher total stock return volatility*

H1a*: Firms in the biotech and pharmaceutical industry with higher R&D investment intensity experience higher total stock return volatility during the COVID-19 pandemic*

R&D investments are highly specific to a particular firm. Therefore, it is expected that the level of R&D intensity will be more closely related to the idiosyncratic part of total volatility. Based on this expectation, the study proposes the following hypotheses:

H2: *Firms in the biotech and pharmaceutical industry with higher R&D investment intensity experience higher idiosyncratic volatility*

H2a*: Firms in the biotech and pharmaceutical industry with higher R&D investment intensity experience higher idiosyncratic volatility during the COVID-19 pandemic*

4. Data and Methodology

4.1 Data

The study examines R&D investments as a potential determinant of stock return volatility of European firms. The sample of firms used in this study is gathered from the Bureau van Dijk's Orbis database. Several requirements must be met to achieve a reliable sample. First, the firm needs to be active from the period 2015 to 2021 and listed on a European Stock Exchange, e.g., Euronext Amsterdam. Second, only firms that are classified into the biotechnology and pharmaceutical industry are included in the sample. These are firms with the following NACE code: 2110, 2120, 7211, 7219, and 7220. NACE is the French abbreviation for the Statistical Classification of Economic Activities in the European Community, which is used by statistical specialists to differentiate between various industries. After cleaning up the data, the sample size in this study consists of 206 firms, and the dataset contains 1442 number of observations. Table A17 provides a list of the complete sample firms in this study. Moreover, data on the monthly adjusted closing price of stocks is gathered from Yahoo Finance.

Moreover, the validity of the results obtained through ordinary OLS regression is dependent upon the satisfaction of several underlying assumptions. One such assumption is the absence of outliers in the data. Outliers can be defined as observations that differ significantly from the rest of the values in the dataset. Given their potential to distort the results, it is important to identify and address these outliers prior to conducting any analysis. To mitigate their impact, the variables in the present study were initially winsorized at the 1% level, both at the lower and upper extremes of the distribution. This method of winsorizing has been utilized in several previous empirical studies, including those by Chen et. al (2011). However, despite this procedure, some outliers remained in the data. Therefore, the variables were winsorized again at the 2.5% level on both sides of the distribution. However, even after this procedure, outliers still persisted in the data. Consequently, the variables were winsorized once more, this time at 5%, which resulted in a reduction in the number of outliers present in the data. The variable "age" is not winsorized because it is a continuous variable that represents an absolute number specific to a single firm. In other words, the age of a firm is a fixed number that cannot be negative or increase by more than one each year. Additionally, dummy variables are not winsorized because they are categorical variables that only have two possible values: 0 and 1. Since these variables cannot include extreme values, there is no need to winsorize them. Winsorizing a dummy variable would not have any effect on its distribution or the regression results.

4.2 Models and regression frameworks

4.2.1 Cross-sectional approach vs Panel data

Fama and French (1996) and Lev and Sougiannis (1996) use a cross-sectional method to regress the monthly stock returns on several fundamental variables hypothesized to explain expected returns. The cross-sectional approach involves analyzing data that is collected at a single point in time from a representative sample of individuals or firms. As opposed to this approach, this study utilizes panel data regression analysis. The panel data regressions are used to investigate whether the explanatory variable (R&D intensity) affect the dependent variable (volatility). Panel data combines time-series and cross-sectional dimensions, allowing data to be analyzed in both ways. This makes it useful for capturing information that cannot be obtained from either time-series or cross-sectional data alone. Therefore, panel data models are better at

capturing information than using a normal time-series or cross-sectional regression. Previous research on the relationship between stock volatility and R&D investments, such as the studies by Gharbi et al. (2014) and Hamim et al. (2020), also used panel data analysis.

4.2.2 Models and variables

There are three different models that can be used to estimate panel data: the pooled regression model, the fixed-effects model, or the random-effects model. Before deciding which model to use, it is important to check for heteroscedasticity in the data. The Breusch-Pagan test can be used to test for the presence of heteroscedasticity, while also determining whether the data is suitable for the random-effects model while the Hausman test us performed to determine whether to use a fixed or random effects model.

4.2.2.1 Pooled OLS regression

Simple linear regression using panel data is called pooled OLS regression. This method only stacks observations for each case over time, ignoring differences across cases and over time. As a result, it does not accurately reflect the relationships between the variables being studied across cases and over time. The results of pooled OLS regression may show statistically significant coefficients, the slope coefficients may have the expected signs, and the R2 value may be relatively high. However, the estimation may also indicate potential autocorrelation in the data, which can be identified using a Durbin-Watson statistic. A low Durbin-Watson statistic indicates a high likelihood of autocorrelation or misspecification of the model (Gil-Garcia & Puron-Cid, 2014). Additionally, OLS regression does not account for endogenous variables.

Pooled OLS applies the same constant α for all the sample firms. The model can be signified as:

$$Y_{it} = \alpha + \beta' X_{it} + \varepsilon_{it} \quad (1)$$

4.2.2.2 Fixed-Effects model

The fixed-effects model examines whether intercepts vary between groups or over time (Hun, 2011). This model postulates that the individual-specific effects are linked to the independent variables. The model investigates individual variations in intercepts, with the assumption that the slopes and constant variance across individuals are unvarying. As an individual-specific effect is time-invariant and a time-specific effect common to all individuals, they are a component of the intercept and therefore can be correlated with other regressors. Thus, the fixed-effects model allows the intercept in the regression model to differ between each specific firm, but not over time. However, the fixed-effects model does have some drawbacks. Beck and Katz (2001) show that time-invariant processes can have effects on time-varying variables, which cannot be assessed in the fixed-effects model. The fixed-effects model is not ideal where there are substantial numbers of case dummies that do not vary on the explained variable during the study period.

The model can be presented as follows:

$$Y_{it} = \alpha_i + \beta' X_{it} + \varepsilon_{it} \quad (2)$$

The coefficients α_i represent unobservable individual firm-specific effects.

4.2.2.3 Random-Effects model

The random-effects model is an alternative to the fixed-effects model. Like the fixed-effects model, the random-effects approach assumes that different firms have different intercepts that are constant over time, and that the relationship between the independent and dependent variables is the same across firms and over time. The difference between the two models is in how they treat dummy variables. In a fixed-effects model, the parameter estimate of a dummy is part of the intercept, while in a random-effects model it is part of the error component (Hun, 2011). One advantage of using the random-effects model is that it allows us to examine variables that are constant over time (Bell et al., 2019). The model assumes that individual effects are random and affect all firms equally. However, there are disadvantages to using the random-effects model. It can produce biased results for models with endogenous variables, meaning that the independent variables are correlated with the error term. In these cases, the fixed-effects model is a better choice. The random-effects model is only appropriate when the error term is not correlated with the independent variables. The Breusch-Pagan test

can help to determine whether the random-effects model is a suitable choice for panel data analysis, given the presence or absence of heteroscedasticity in the data.

The constant can be written in the following form:

$$\alpha_i = \alpha + u_i$$

The random effects model is presented as follows:

$$Y_{it} = \alpha_i + \beta' X_{it} + u_i + \varepsilon_{it} \quad (3)$$

4.2.2.3 Fixed-Effects model vs. Random-Effects model

The choice between the fixed and random effects models is made using the Hausman test. The Hausman specification test is a test for endogeneity, or correlation, in the error term, and is used to determine whether the random-effects model is appropriate for the panel data. The null hypothesis in the Hausman test is that there is no endogeneity, meaning that the error term is uncorrelated with the independent variables. In this case, the random-effects model is appropriate for the analysis. However, if the null hypothesis is rejected, indicating the presence of endogeneity, the fixed-effects model is preferred over the random-effects model, as the former can control for unobserved individual-specific effects (Rachev et al., 2007).

4.3 Variables

Idiosyncratic volatility

The dependent variable in this study is stock volatility. By nature, the true volatility is unobserved. It remains an ongoing debate regarding what the appropriate proxy of volatility is. Idiosyncratic volatility, also known as firm-specific risk, is the risk that is particular to a firm or industry. The idiosyncratic volatility component is only implicitly observable by determining the volatility of the residuals, i.e., the error-term from an asset pricing model.

Previously, researchers have used various proxies to measure idiosyncratic volatility. For example, Mazzucato and Tancioni (2012) used the log ratio between the standard deviation of a firm's return and the average industry return standard deviation as a proxy for idiosyncratic risk. Gharbi et al. (2014) used the CAPM model by Sharpe (1964) and calculated idiosyncratic stock volatility as the annualized standard deviation of weekly errors using the CAPM model.

This study also uses the CAPM model, with idiosyncratic volatility calculated as the annualized standard deviation of monthly errors.

The estimation will follow the equation below:

$$R_{it} = R_f + \beta_{im}(R_{mt} - R_f) + \varepsilon_{it} \quad (4)$$

With,

R_{it} = The return for firm i

R_f = The risk-free rate

R_{mt} = The market return

ε_{it} = The error term

The asset's variance can be broken down using the Sharpe-Lintner CAPM equation:

$$\sigma_i^2 = \beta_i^2 \sigma_m^2 + \sigma_\varepsilon^2$$

Residual sequence ε_{it} is assumed as white noise, which is a normal distribution with zero and variance σ_ε^2. The risk-free rate is estimated using the monthly risk-free return of each country's historical long-term government bonds over the study period, which is gathered from the European Central Bank[5]. Table A18 provides an overview of the risk-free rates per year for each European country in the study.

Total stock volatility

The total volatility is determined based on the annualized standard deviation of monthly return for each year. The methodology used is comparable to the traditional volatility calculation described as historical volatility. In other practices, the formula is used to measure standard deviation, while in many finance and investment literatures, standard deviation and volatility are used interchangeably.

[5] Financial Markets and Interest Rates - Reports - ECB Statistical Data Warehouse. https://sdw-ecb-europa-eu.ezproxy2.utwente.nl/browse.do?node=bbn4864

To find the volatility of stocks return, I will compute the standard deviation of monthly returns using the following formula:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2} \quad (5)$$

Where, μ is the mean value of the monthly returns.

To compute the annualized standard deviation, the monthly standard deviation obtained will be multiplied by the square root of 12. Consequentially, the annualized standard deviation is calculated as follow: $Annualized\ \sigma = \sigma\sqrt{12}$ (6)

R&D investment intensity

Previously, researchers have used various proxies to measure R&D investment intensity. For instance, Ugur et al. (2016) used the logarithm of R&D expenses as a proportion of turnover (R&D/turnover ratio) as a proxy for R&D intensity. Gharbi et al. (2014) defined R&D intensity as the ratio of R&D expenses to sales. Bansal et al. (2016) measured R&D intensity as the ratio of R&D expenses to total assets. The ratio of R&D expenses to sales has been the most commonly used measure. In this study, R&D intensity is the independent variable and is measured by dividing R&D expenses by the firm's sales. Table 1 provides definitions and abbreviations for all the variables. As a robustness check, R&D intensity will also be calculated as the ratio of R&D expenses to total assets.

Following the study of Gharbi et al. (2014), this paper uses the control variables 'size' and 'leverage.' In addition, this paper includes the control variable 'firm age' and lastly the dummy variable ‘COVID-19 period indicator' to analyze the impact of COVID-19 on volatility during the COVID-19 pandemic.

Table 1: Definitions of variables

Variable name	Abbreviation	Definition
Idiosyncratic Volatility	IVOL	Annualized standard deviation of monthly errors
Total Stock Volatility	TSVOL	Annualized standard deviation of monthly return
R&D Investment Intensity	RDII_1	Ratio of R&D expenditures to sales
Size	SIZE	Natural logarithm of total assets
Firm Age	AGE	Natural log of the age of the firm since its establishment
Leverage	LVRG	Ratio of total debts to total assets
COVID-19 period indicator	COVID	0 = pre-COVID-19, 1= during COVID-19

Size

Firm size is an important determinant of a firm's ability to invest in R&D because larger firms typically have greater financial resources, which they can use to fund R&D activities. Additionally, larger firms may have more established networks of suppliers, customers, and other partners, which can provide them with access to valuable knowledge and expertise. Furthermore, larger firms may be able to spread the costs of R&D over a larger base of sales, which can help to make their R&D investments more affordable. As a result, larger firms may be better positioned to undertake R&D activities, which can help them to develop new products and services, increase their competitiveness, and achieve long-term growth. Additionally, larger firms tend to have greater financial analyst coverage than smaller firms. This implies that smaller firms may experience greater information asymmetry compared to larger firms. Firm size is measured using the natural log of total assets, as in Tebourbi et al. (2020).

Firm Age

Older firms may have stronger networks of suppliers, customers, and other partners, providing them with access to valuable knowledge and expertise. In contrast, younger or smaller firms may face financial constraints (Czarnitzki, 2006). Furthermore, older firms may also have more experience in conducting R&D, which can help them to develop new products and services more efficiently and effectively. Additionally, older firms may have a successful track record in R&D, which can help them to secure funding from investors, and may have a

reputation for innovation, which can attract top talent. Overall, older firms may be better positioned to undertake R&D and achieve long-term growth. Following Tebourbi et al. (2020), firm age is measured by the natural log of years since establishment.

Leverage

Firms with higher levels of leverage may be less able to fund R&D activities, as they may have more limited access to financial resources due to their debt obligations. As a result, firms with higher leverage may be less able to invest in R&D, which can limit their ability to develop new products and services and achieve long-term growth Moreover, firms with higher levels of leverage may also face greater financial risks, as they may be more vulnerable to economic downturns or changes in market conditions. This can create uncertainty and discourage firms from investing in R&D, as they may be more focused on managing their debt and reducing their financial risks.

Different proxies, or methods, can be used to calculate leverage. For example, Kothari et al. e the sum of long-term debt and debt in current liabilities divided by the sum of long-term debt and the market value of equity. In this study, leverage is calculated by dividing total debt by total assets. Several studies have used this proxy as a control variable in their research. Ghabri et al. (2014) and Bansal et al. (2016) are examples of studies that have used this proxy in their research.

COVID-19 period indicator

The variable "COVID-19 period indicator" is a dummy variable taking the value of zero if the observation year is the year pre-COVID-19 (2015 and 2019) and 1 if the observation year is the year during the COVID-19 periods (2020-2021).

4.4 Research model

This study examines the relationship between R&D investment and stock return volatility. Since the study comprises two measures for the dependent variable 'stock return volatility' (IVOL and TSVOL), two different models are utilized. Both models consist of seven

variables: one dependent variable, one independent variable, four control variables, and one interaction variable. The following model (1) is used in this study to estimate the link between R&D investment and total stock return volatility, i.e., to test hypotheses 1 and 1a:

$$TSVOL_{it} = \beta_0 + \beta_1(RDII\_1)_{it} + \beta_2(SIZE)_{it} + \beta_3(AGE)_{it} + \beta_4(LVRG)_{it} + \beta_5(COVID)_{it} + \beta_6(RDII\_1)_{it} \times (COVID)_{it} + \varepsilon_{it}$$

In order to test hypotheses 2 and 2a, which estimate the link between R&D investment and idiosyncratic volatility, the following model (2) is used:

$$IVOL_{it} = \beta_0 + \beta_1(RDII\_1)_{it} + \beta_2(SIZE)_{it} + \beta_3(AGE)_{it} + \beta_4(LVRG)_{it} + \beta_5(COVID)_{it} + \beta_6(RDII\_1)_{it} \times (COVID)_{it} + \varepsilon_{it}$$

Where,

$TSVOL_{it}$= Total stock return volatility of firm i in year t

$IVOL_{it}$= Idiosyncratic volatility of firm i in year t

β_0= Intercept

$RDII\_1_{it}$= R&D investment intensity of firm i in year measured as ratio of R&D expenditures to sales

$RDII\_2_{it}$= R&D investment intensity of firm i in year measured as the ratio of R&D expenses to total assets

$SIZE_{it}$= Control variable size of firm i in year t

AGE_{it}= Control variable age of firm i in year t

$LVRG_{it}$= Control variable leverage of firm i in year t

$COVID_{it}$= Control variable COVID-19 period indicator dummy for year t

ε_{it}= Error term of firm i in year t

The interaction term $\beta_5(R\&D)_{it} \times (COVID)_{it}$ captures the differential effects between R&D investments on stock return volatility post and during COVID-19. In this regard, COVID is a dummy variable which is equal to '0' if the study period is pre-COVID-19 (2015-2019) and 1 if the study period is during COVID-19 (2020).

4.5 Descriptive Statistics

This chapter discusses the results of the descriptive statistics in the study. As outlined in section 4.3, a 5% winsorization technique was applied to address the presence of outliers in the dataset. Table 2. provides an overview of the descriptive statistics of the variables under examination in the study. For a more detailed breakdown of the descriptive statistics for the pre and during COVID periods, refer to Table A1 and A2 in the appendix.

The results of the analysis (Table 2.) indicate that the volatility measures are high. The average (median) values of total stock volatility (TSVOL) and idiosyncratic stock volatility (IVOL) are 50.04% (42.83%) and 50.16% (43.10%) respectively. These results mean that, on average, the total stock volatility and idiosyncratic stock volatility of the sample firms are very similar. Gharbi et al. (2008) found similar outcomes to this study, with mean values of 49.10% for TSVOL and 46.90% for IVOL, affirming the consistency between their study and the present analysis.

Table 2: Descriptive Statistics of Variables

	N	Mean	Median	SD	Min	Max
TSVOL	1443	.5	0.428	.282	.166	1.244
IVOL	1446	.502	0.431	.258	.203	1.168
RDII 1	1388	1.849	0.095	4.518	0	18.778
RDII 2	1540	.116	0.463	0.157	0	0.542
LVRG	1540	.399	0.367	.265	.056	.989
SIZE	1540	4.888	4.751	1.044	3.271	7.118
AGE	1540	26	17	31	0	203

Notes: This table presents the summary statistics of the variables used in this research. All variables, except for "age," have been winsorized at the 5% level. Variable definitions are described in Table 1.

Furthermore, the study examines the R&D investment intensity (RDII) of European pharmaceutical and biotechnology firms and the results suggest that these firms invest a substantial amount of their sales in R&D. On average, the firms in the sample invest nearly two times their sales in R&D, which indicates that they prioritize innovation and the development of new products. In contrast to the findings of Mazzucato and Tancioni (2012), the R&D intensity observed in this study is significantly higher. Mazzucato and Tancioni reported a mean R&D intensity of 0.119 (11.9%), which differs from the higher levels found for RDII_1 in the present study. However, when comparing their mean value for R&D intensity with RDII_2, which has a mean value of 0.116 (11.6%), we observe a similar consistency.

It is important to note that a significant proportion of firms in the study did not invest in R&D at one point in time, as indicated by 427 observations with zero R&D investment, which correspond to 85 distinct firms.

Moreover, the control variables are also examined. For instance, the mean and median for leverage (LVRG), which indicates the proportion of a firm's total assets that are financed by debt, is 39.9% of their total assets, with a range from 5.60% to 98.90%. The mean value of (SIZE), measured by the firms' total asset's natural logarithm, is 4.888, which transformed into their real values they will become € 132.687,93, € 26.337,66, and 1.233.980,00 for the mean, minimum and maximum values, respectively. This suggests that there is a wide range of firm sizes in the sample, with some firms being significantly larger or smaller than the average.

Finally, the variable firm age (AGE) represents the number of years since the establishment of each firm in the sample. The results show that the mean age of the firms is 26 years, with a median of 17 years. This suggests that the distribution of firm ages is slightly skewed towards younger firms, as the median age is lower than the mean age. The standard deviation of 31 and the minimum age of the firms in the sample is 0 years, while the maximum age is 203 years, highlighting the significant variation in the age of the firms in the sample. Overall, the summary statistics suggest that there is a diverse mix of both young and established firms in the sample, with some firms being relatively young and others being more mature. This could have implications for the analysis and interpretation of the results, as the age of firms may influence their behavior and performance. For instance, younger firms may be more innovative and adaptable, but may also face financial constraints that limit their ability to invest in R&D (Czarnitzki, 2006). In contrast, older firms may have more established market positions and resources, as suggested by Tebourbi et al. (2020), and may have a successful track record in R&D, which can help them secure funding from investors and attract top talent. Therefore, the age of firms can impact their ability to undertake R&D projects.

5.0 Empirical results

This chapter presents the empirical findings obtained from the study. The initial section of the chapter presents the Pearson's correlation matrix. The second section is dedicated to evaluating whether the assumptions of the OLS regression analysis have been fulfilled. Meanwhile the third section discloses the results and discussions of the Breusch-Pagan and Hausman test, and

panel data regression analysis. Lastly, the empirical results section concludes with the execution of robustness tests aimed at evaluating the reliability and consistency of the regression analysis findings.

5.1 Pearson's correlation matrix

This section presents an analysis of the Pearson's correlation matrix as presented in Table 3. The correlation coefficients in the matrix range from -1 to +1, indicating the strength and direction of the relationship between two variables. Negative coefficients indicate an inverse relationship, while positive coefficients imply a direct relationship. Correlation coefficients above .50 or .70 are commonly considered high and indicate strong relationships, whereas values between .30 and .50 are indicative of moderate relationships. Correlations below .30 are typically regarded as small, and values below .10 suggest weak relationships.

The correlation coefficient between total stock volatility (TSVOL) and idiosyncratic stock volatility (IVOL) is strong and positive (0.963), indicating that the variables are highly related to each other. However, it is important to note that both TSVOL and IVOL are dependent variables in the study. Moreover, R&D investment intensity (RDII_1) has a weak positive correlation with TSVOL (0,141) and IVOL (0,127). This indicates that there is a small positive association between R&D investment and stock volatility, which suggest that an increase in R&D investment intensity is linked to a rise in stock volatility, which is consistent with the study's hypothesis that increased investment intensity has an impact on stock return volatility.

Table 3: Pearson correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) TSVOL	1.000						
(2) IVOL	0.963***	1.000					
(3) RDII_1	0.141***	0.127***	1.000				
(4) LVRG	-0.028	-0.032	-0.126***	1.000			
(5) SIZE	-0.387***	-0.361***	-0.101***	0.193***	1.000		
(6) AGE	-0.288***	-0.271***	-0.179***	0.090***	0.470***	1.000	

Notes: This table presents Pearson's correlation between variables used in this study. Variable definitions are described in table 1. *** *p<0.01, ** p<0.05, * p<0.1*

Furthermore, firm size (SIZE) has a negative correlation with TSVOL (-0.387) and IVOL (-.361), meaning that larger firms tend to have lower idiosyncratic volatility and total stock volatility. Regarding firm age (AGE), the results show that the correlation between AGE and IVOL is negative (-0.271), indicating that as firms get older, their idiosyncratic stock volatility tends to decrease. Similarly, the negative correlation (-0.288) between AGE and TSVOL implies that older firms tend to have lower total stock volatility. Additionally, the variable leverage (LVRG) has a moderate negative correlation with RDII_1 (0.126), implying that as firms increase their leverage, they invest less in R&D, which can limit their ability to develop new products and services and achieve long-term growth. However, correlation does not imply relationships. Hence, we will test if there is a statistical relationship through regression analysis as shown in section 6.3.1 and 6.3.2.

5.2 OLS regression assumptions

To ensure the reliability and validity of the results, it is important to satisfy several OLS regression assumptions prior to running the regression models in the study. The results discussed in this section have been tested and found to be valid for both research models in our study, i.e., for Total Stock Volatility (TSVOL) and Idiosyncratic Volatility (IVOL).

In chapter 4.2.2.1, we shortly explained possible autocorrelation in the data, this is a violation of the *independence assumption* in OLS regression, which assumes that the error terms are independent and identically distributed. Autocorrelation occurs when the error-terms are correlated with each other, which means that the error term at one point is related to the error-term at a previous time point. Given that the present study employs panel data, the Woolridge test is utilized to examine the presence of autocorrelation. The Wooldridge test is based on the first-order autocorrelation coefficient, denoted as ϱ (Drukker, 2003). The null hypothesis of the test is that $\varrho=0$, meaning there is no autocorrelation in the errors. The alternative hypothesis is that $\varrho\neq0$, indicating that there is autocorrelation present. The test results for both TSVOL and IVOL reveal that there is evidence to assume that there is autocorrelation in the panel data (p-value= 0.031<0.05) and (p-value=0.009<0.01) (Table A3 and A4.). To correct for the impact of autocorrelation on the estimates, robust standard errors clustered at firm level will be used, which adjust the standard errors of the parameter estimates to account for the correlation structure of the panel data (Hoechle, 2007).

Besides the independence assumption, there are other key assumptions of the OLS regression method that must be met, these are the homoscedasticity, linearity, normality, and multicollinearity. The *homoscedasticity assumption* states that the variance of the error terms is constant across all levels of the independent variables i.e., the spread of the residuals should be the same throughout the range of predicted values. Violation of the homoscedasticity assumption is known as heteroscedasticity, which can lead to biased and inefficient estimates of the regression coefficients and incorrect hypothesis tests and confidence intervals. To test for heteroskedasticity, this study will use the White's test. The White's test involves estimating the OLS regression equation and regressing the squared residuals on the independent variables and their squares. The null hypothesis assumes that there is homoscedasticity, meaning that the error term's variance is constant across all levels of the independent variables. The alternative hypothesis assumes that there is unrestricted heteroscedasticity, meaning that the error term's variance differs across levels of the independent variables. The result of White's test suggests that we reject the null hypothesis of homoscedasticity and conclude that there is evidence of heteroscedasticity in the error term's variance for both TSVOL (chi2(23), N= 1320) = 102.43 p-value<0.001) and IVOL (chi2(23), N= 1320) = 107.64 p-value<0.001) (Table A5 and A6.). To address the issue of heteroscedasticity in the error terms, robust standard errors, which are used to correct for autocorrelation in panel data, will also be used[6]. So, we will employ robust standard errors to address both heteroscedasticity in the error terms and autocorrelation in the panel data.

Moreover, the *linearity assumption* states that the relationship between the independent variables and the dependent variables is linear i.e., the effect of one-unit change in an independent variable on the dependent variable is constant across the range of the independent variable. There are several tests that can be used to detect nonlinearity in OLS regression. One common approach, which is the one that will be used in this study, is the use scatter plots to visualize the relationship between the independent variables and the dependent variable. After examining the scatterplots presented in Appendix Figures A1 and A2, it seems that no significant correlations exist between the dependent variable and the independent variables, suggesting that the linearity assumption of OLS may be valid. Another approach is to use residual plots, which plot the residuals against the predicted values. If the residuals show a

[6] For e detailed explanation on heteroskedasticity-robust standard errors please refer to Woolridge (2010, pp. 177-178).

pattern, such as a curved of U-shaped pattern, this may indicate that the relationship between the variables is nonlinear.

Furthermore, in OLS regression, the *assumption of normality* refers to the assumption that the errors (residuals) are normally distributed. This is a crucial assumption in OLS because if the errors are not normally distributed, the OLS estimates may be biased, inefficient, or even completely wrong. Normality means that that the distribution of the errors follows a normal distribution, which is a bell-shaped curve. The normal distribution is characterized by two parameters: the mean (μ) and the standard deviation (σ). In a normally distributed sample, the mean and median are the same, and 68% of the observations fall within one standard deviation of the mean. There are several tests that can be used to detect whether the errors in a regression model are normally distributed. However, the distribution of stock returns is known to be non-normally distributed because of their heavy-tailed and highly skewed distribution. This non-normality is primarily due to the heteroskedasticity of stock returns[7]. Furthermore, a histogram of the distribution of the residuals, which is also a way of inspecting the normality assumption (Figure A3).

Lastly, *multicollinearity* is a statistical phenomenon in which two or more predictor variables in a regression model are highly correlated with each other. This can lead to unreliable estimates of the regression coefficients, making it difficult to draw meaningful conclusions about the relationship between the independent variables and dependent variable. One way to detect multicollinearity is to use the Variance Inflation Factor (VIF) test, which is the test that is used in this study. The VIF is a measure of how much the variance of the estimated regression coefficient is increased due to the presence of collinearity among the predictor variables. The VIF for a predictor variable is calculated as follows:

$$VIF = 1 / (1 - R^2)$$

Where R^2 is the coefficient of determination obtained from a regression of the predictor variable against all the other predictor variables in the model. The VIF ranges from 1 to infinity, with a VIF of 1 indicating no collinearity, and a VIF of greater than 1 indicating increasing levels of collinearity. A common rule of thumb is that a VIF of 5 or greater indicates a high level of collinearity and may require further investigation. In practice, if multicollinearity is detected, it may be necessary to consider removing one or more of the highly correlated

[7]For e detailed explanation on the distribution of stock return volatility please refer to Andersen et al. (1996).

predictor variables from the model or transforming the predictor variables to reduce their correlation. The result of the VIF test suggests that there is no significant multicollinearity among the predictor variables in the regression model. The highest VIF value is 1.27, which is well below the threshold of 5 (Appendix Table A7 and A8). Therefore, it can be concluded that there is no significant multicollinearity among the predictor variables, and the regression coefficients can be interpreted with confidence.

5.3 Regression results

This section focuses on the results and discussion of the regression analysis using panel data. In the first instance, a pooled OLS regression model is estimated. However, it is essential to note that pooled OLS regression assumes that the effects of independent variables remain constant across all individuals and time periods, which may not hold for panel data, thereby leading to biased results[8]. To test for this, the Breusch-Pagan Lagrange Multiplier (LM) test is performed. The Breusch-Pagan LM is a statistical test that is used in panel data analysis to assess the significance of random effects. The null hypothesis explains the pooled regression model is appropriate against the alternative hypothesis which explains the random effect model is appropriate. To make a definitive choice between fixed and random effects models, a Hausman test is performed. If the Hausman test supports the random effects model (i.e., fails to reject the null hypothesis), it would indicate that the random effects model is preferred. If the Hausman test favors the fixed effects model (i.e., rejects the null hypothesis), it suggests that the fixed effects model is more appropriate.

5.3.1 Effects of R&D investment intensity on the total stock return volatility (TSVOL)

After performing the Breusch-Pagan LM test for random effects, the results indicate strong evidence to reject the null hypothesis for both TSVOL (chibar2(01) = 105.14, p-value <0.001) and IVOL (chibar2(01) = 88.85, p-value <0.001) (Table A15 and A16) These findings suggest that the random effects model may be appropriate for the dataset. However the Hausman test can determine which model best fits the data, hence, the Hausman test was also performed, and its results show that there is no significant presence of random effects. So, based on the Hausman test, the fixed-effects model is the appropriate choice for the dataset compared

[8] For a detailed explanation on panel data, please refer to Schmidheiny (2022).

to the random effects model (Table A13). Therefore, to avoid bias that could arise from ignoring individual-specific and time-specific effects, the fixed-effects model is employed for the regression analysis and its results will be discussed in this section.

Table 4 presents the regression results that examine the link between R&D investment and total stock return volatility. Specifically, the results correspond to the hypotheses 1 and 1a. Hypothesis 1 propose that firms with higher R&D investment intensity tend to experience higher total stock return volatility, and hypothesis 1a suggests that firms with higher R&D investment intensity experience higher total stock return volatility during the COVID-19 pandemic.

Table 4. Effects of R&D investment intensity on the total stock return volatility (TSVOL)

VARIABLES	(1) Pooled	(2) FE	(3) RE
RDII_1	0.00498***	-0.00466*	0.00178
	(0.00179)	(0.00405)	(0.00272)
LVRG	0.0811***	0.0160	0.0602
	(0.0272)	(0.0684)	(0.0435)
SIZE	-0.0890***	-0.123**	-0.0925***
	(0.00743)	(0.0517)	(0.0122)
AGE	-0.00110***	-0.00488	-0.00121***
	(0.000238)	(0.00548)	(0.000321)
COVID	0.102***	0.114***	0.1000***
	(0.0161)	(0.0253)	(0.0160)
RDCOV	0.00407	0.00625*	0.00499
	(0.00355)	(0.00491)	(0.00480)
Constant	0.890***	1.208***	0.930***
	(0.0360)	(0.263)	(0.0590)
Observations	1,317	1,317	1,317
R-squared	0.206	0.056	
Number of B		212	212

Notes: This table presents the estimated coefficients from regressing total stock volatility (TSVOL) on R&D investment intensity (RDII_1) and several control variables. TSVOL is the dependent variable, while RDII_1 is the independent variable. The control variables include LVRG, SIZE, AGE, and COVID, while RDCOV is the interaction term that captures the differential effects of R&D investments on stock return volatility during and post-COVID-19. Number of B refers to the number of unique firm-level clusters in the fixed effects regression. Standard errors are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1.

5.3.1.1 Pooled OLS (1) model TSVOL

The results in Table 4 of the pooled OLS shows that the coefficient estimate for the relationship between R&D investment intensity and total stock return volatility is 0.005, which is positive and significant 1% level. This result provides support for hypothesis 1 and indicates that firms with higher R&D investment intensity tend to experience higher total stock return

volatility. However, the interaction term RDCOV is not statistically significant, implying that companies with higher R&D investment intensity did not experience increased total stock return volatility during the COVID-19 pandemic. Thus, there is insufficient evidence to support hypothesis 2a.

The findings pertaining to the control variables are aligned with the theoretical expectations and prior empirical literature. The control variable LVRG is positive and significant, which is in line with the positive association reported by Gharbi et al. (2014). This implies that firms with higher leverage ratios tend to have higher total stock return volatility. As a result, firms with greater leverage may have limited capacity to invest in R&D, hindering their ability to create new products and services and achieve sustainable growth. Additionally, this result suggests that firms with higher levels of leverage may face greater financial risks, as they may be more vulnerable to economic downturns or changes in market conditions.

Moreover, the control variable SIZE is statistically negatively significant. This is in line with the findings of Gharbi et al. (2014) who also observed a similar association with the variable SIZE. Lastly, firm age (AGE) is statistically negatively significant, indicating that as firms get older, their total stock return volatility tends to decrease. This may be because younger or smaller firms may face financial constraints while older firms have valuable knowledge and expertise in conducting R&D (Czarnitzki, 2006).

However, as stated above, the result of the Breusch-Pagan test confirm that the panel data is not poolable, therefore, the results of the pooled OLS regression is biased. Hence, the focus will now be placed on the results of the fixed effects model, which appears to be the most appropriate for our dataset.

5.3.1.2 Fixed effects (2) model TSVOL

As previously discussed, both the Breusch-Pagan LM test and Hausman tests have confirmed the appropriateness of the fixed effects over the random effects model for our panel data regression. Furthermore, a panel heteroskedasticity test was conducted on the fixed effects model, which revealed the presence of heteroskedasticity in the model. To address this issue, robust standard errors is employed, which are commonly used to adjust for autocorrelation in panel data analysis. However, the presence of autocorrelation in the panel data was also detected. To account for the impact of autocorrelation on the estimates, robust standard errors clustered at the firm level is used,1, which is a method frequently used in panel data analysis to

account for correlated errors within each firm[9]. This approach will allow accurate standard errors to be obtained, which are crucial for reliable inference and hypothesis testing. The results obtained from the fixed effects model are presented in this section.

The results of the fixed effects model indicate that R&D investment intensity (RDII_1) has a statistically significant negative effect on total stock return volatility (-0.005, p-value<0.10). Indicating that if RDII_1 increases by 1 unit, the total stock return volatility would decrease by -0.005. The mean of R&D investment (RDII_1) is 1.849. This suggests that, on average, firms in the pharmaceutical and biotechnology sector allocate a significant portion of their revenue to R&D activities. Furthermore, the standard deviation of RDII_1 is 4.158. Multiplying this value by -0.005 gives us -0.021. Consequently, the new total volatility would be approximately 2.1% lower than the previous volatility level. These findings suggests that an increase in R&D investment leads to a decrease in total stock return volatility, while controlling for other variables. Therefore, we find weakly significant results opposing hypothesis 1, which suggests that firms with higher R&D investment intensity will experience greater total stock return volatility. However, the R-squared value is low (0.056), indicating that the model does not explain a significant proportion of the variation in the dependent variable. The control variables LVRG and AGE are not statistically significant in explaining the total stock return volatility.

Additionally, the interaction term RDCOV was examined to investigate the differential effects of R&D investments on stock return volatility during and after the COVID-19 period. The results indicate that RDCOV has a positive but weak effect on total stock return volatility (0.006, p-value<0.10). This suggests that an increase of one unit in RDII_1 during the COVID-19 pandemic corresponds to a 0.00625 increase in total stock return volatility, approximately 0.625%. So, the fixed effects results suggest, firms with higher R&D investment intensity experience lower volatility in their stock returns overall, but during the COVID-19 pandemic period, they have experienced higher volatility in their total stock return. Therefore, hypothesis 2a, which proposes that firms with higher R&D investment intensity experience higher total stock return volatility during the COVID-19 pandemic, is supported by the analysis at 10% significant level. This result lends credence to the results of Bora et al. (2021) and Liu et al. (2020) which also documented higher market volatility and lower investor confidence during the pandemic.

[9] [9] For a detailed explanation on panel data, please refer to Cameron et al. (2015)

5.3.2 Effects of R&D investment intensity on the stock idiosyncratic volatility (IVOL)

Likewise, the results of the TSVOL, the Breusch-Pagan LM test for IVOL indicate that the null hypothesis of constant variance of the error term is rejected at a high level of significance (chibar2(01) = 88.85, p-value<0.001). Hence, the OLS regression model is not appropriate for the panel data (Table A16). The results of the Hausman test support the previous finding, indicating that the fixed-effects model is the appropriate choice for the dataset (Table A14). To account for individual-specific and time-specific effects and prevent any resulting bias, the regression analysis utilizes the fixed-effects model, and its results are presented in this section.

Table 5 presents the regression results that examine the link between R&D investment and idiosyncratic volatility. Specifically, the results correspond to the hypotheses 2 and 2a. Hypothesis 2 propose that firms with higher R&D investment intensity tend to experience higher idiosyncratic volatility, and hypothesis 2a suggests that firms with higher R&D investment intensity experience higher idiosyncratic volatility during the COVID-19 pandemic.

Table 5. Effects of R&D investment intensity on the stock idiosyncratic volatility (IV)

VARIABLES	(1) Pooled	(2) FE	(3) RE
RDII_1	0.00374**	-0.00413	0.00120
	(0.00164)	(0.00365)	(0.00236)
LVRG	0.0621**	0.00102	0.0446
	(0.0249)	(0.0608)	(0.0383)
SIZE	-0.0755***	-0.112**	-0.0784***
	(0.00682)	(0.0475)	(0.0106)
AGE	-0.000975***	-0.00257	-0.00106***
	(0.000219)	(0.00508)	(0.000294)
COVID	0.107***	0.109***	0.103***
	(0.0148)	(0.0228)	(0.0140)
RDCOV	0.00465	0.00675	0.00556
	(0.00325)	(0.00431)	(0.00421)
Constant	0.830***	1.096***	0.864***
	(0.0330)	(0.241)	(0.0515)
Observations	1,320	1,320	1,320
R-squared	0.194	0.065	
Number of B		212	212

Notes: This table presents the estimated coefficients from regressing idiosyncratic volatility (IVOL) on R&D investment intensity (RDII_1) and several control variables. IVOL is the dependent variable, while RDII_1 is the independent variable. The control variables include LVRG, SIZE, AGE, and COVID, while RDCOV is the interaction term that captures the differential effects of R&D investments on stock return volatility during and post-COVID-19. Number of B refers to the number of unique firm-level clusters in the fixed effects regression. Standard errors are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1.

5.3.2.1 Fixed effects model

The fixed effects model was deemed appropriate for our panel data regression as confirmed by both the Breusch-Pagan and Hausman tests, which were discussed earlier. However, a heteroskedasticity test on the fixed effects model for IVOL indicated the presence of heteroskedasticity. Robust standard errors clustered at firm level were used to address the issue of heteroskedasticity. Additionally, the presence of autocorrelation in the panel data was identified, and clustering at the firm level was employed as a solution.

In contrast to the results of the pooled OLS model, the independent variable RDII_1 fails to achieve statistical significance at any level, indicating that a higher level of R&D investment intensity does not necessarily lead to an increase in idiosyncratic volatility. The findings suggest that R&D investment intensity does not have any explanatory power on idiosyncratic volatility after controlling for the variables of leverage, firm size, and firm age. Therefore, hypothesis 2, which suggests that firms with higher R&D investment intensity experience greater idiosyncratic volatility, is not supported by the analysis. In other words, firms with higher R&D investment intensity does not experience higher idiosyncratic volatility. This finding contrasts with the results of Gharbi et al. (2014), who reported a positive relationship between idiosyncratic volatility and R&D intensity.

Furthermore, the interaction term RDCOV was also examined to investigate the differential effects of R&D investments on stock return volatility post and during COVID-19. However. the results show that RDCOV is statistically insignificant. As a result, hypothesis 2a, which proposes that firms with higher R&D investment intensity experience higher idiosyncratic volatility during the COVID-19 pandemic, is not supported by the analysis. Moreover, in the fixed effects model, the variable SIZE is the only statistically significant variable, indicating that larger firms tend to have lower idiosyncratic volatility. This finding is in line with the theoretical expectations and previous empirical evidence discussed by Gharbi et al. (2014).

Moreover, the negative relationship observed between R&D intensity and TSVOL suggests that higher R&D investment leads to a decrease in overall stock return volatility. This could be due to R&D activities enhancing firm performance, reducing uncertainty, and increasing market confidence, thereby resulting in lower TSVOL. On the other hand, IVOL focuses solely on the idiosyncratic or firm-specific volatility component, which may be influenced by factors other than R&D intensity, such as firm-specific events, market sentiment,

or industry dynamics. Consequently, the lack of significant results for IVOL may indicate that R&D intensity does not have a noticeable impact on firm-specific volatility.

5.4 Robustness test

As discussed in Chapter 4, Section 4.3, scholars have used various proxies to measure R&D investment intensity. To enhance the robustness of the analysis, an alternative measure of R&D intensity will be incorporated in this study. Specifically, the ratio of R&D expenses to total assets (RDII_2) will be employed to gauge R&D investment intensity.

The goal of including this additional measure is to confirm and strengthen the results obtained using the initial measure of R&D investment intensity (RDII_1). This helps in checking whether the relationship between R&D investment intensity and the variable in the study remains consistent when different measures are used. Using multiple measures improves the trustworthiness of the study's conclusions and provides a better understanding of how R&D investment affects stock return volatility.

It is important to note that the same steps used in Section 6.3 for the regression analysis of panel data was followed. After performing these necessary steps, it was determined that the fixed-effects model is the appropriate choice for the dataset. Therefore, the fixed-effects model is utilized for the robustness regression analysis, and the results are discussed in this section.

Additionally, to address the potential distortion caused by the capped values of total stock return volatility (TSVOL) and idiosyncratic volatility (IVOL) (Figures A1 and A2), an additional analysis was conducted. Following the approach used by Gharbi et al. (2006) in their study, this analysis incorporates the natural logarithm (LN) of TSVOL and IVOL as independent variables in the regression model.

5.4.1 Robustness test Fixed effects model (TSVOL)

The results of the robustness test regression, as presented in Table 5, shows the findings regarding the relationship between R&D investment intensity (RDII_2) and total stock return volatility (TSVOL). The fixed effects model shows that RDII_2 has a statistically significant negative effect on TSVOL (-0.251, p-value < 0.05), suggesting that an increase of 1 unit in RDII_2 corresponds to a decrease in total stock return volatility by 0.251. The standard

deviation of RDII_2 is 0.116. Multiplying this value by -0.251 yields -0.029. Consequently, the new total volatility would be approximately 2.90% lower than the previous total stock return volatility level. This suggests that an increase in R&D investment leads to a decrease in total stock return volatility, even after considering other variables. Among the control variables, LVRG and AGE do not exhibit statistical significance in explaining TSVOL. On the other hand, the variable SIZE is statistically significant (0.152, p-value < 0.001), indicating that larger firms tend to have lower total stock volatility. However, the interaction term RDCOV does not show statistical significance.

Table 5. Robustness test: effects of R&D investment intensity on the total stock return volatility (TSVOL)

VARIABLES	(1) Pooled	(2) FE	(3) RE
RDII_2	0.124**	-0.251**	0.0350
	(0.0516)	(0.117)	(0.0706)
LVRG	0.0421	0.0839	0.0499
	(0.0259)	(0.0678)	(0.0404)
SIZE	-0.0905***	-0.152***	-0.0930***
	(0.00734)	(0.0473)	(0.0119)
AGE	-0.00115***	-0.00305	-0.00121***
	(0.000240)	(0.00536)	(0.000312)
COVID	0.0940***	0.0992***	0.0897***
	(0.0179)	(0.0269)	(0.0181)
RDCOV	0.116	0.142	0.140
	(0.0948)	(0.127)	(0.118)
Constant	0.915***	1.294***	0.938***
	(0.0352)	(0.232)	(0.0581)
Observations	1,443	1,443	1,443
R-squared	0.206	0.059	
Number of B		220	220

Notes: This table presents the results of the robustness test aimed at investigating the relationship between total stock return volatility (TSVOL) and R&D investment intensity (RDII_2), and several control variables. TSVOL is the dependent variable, while RDII_2 is the independent variable. The control variables include LVRG, SIZE, AGE, and COVID, while RDCOV is the interaction term that captures the differential effects of R&D investments on stock return volatility during and post-COVID-19. Number of B refers to the number of unique firm-level clusters in the fixed effects regression. Standard errors are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1.

In summary, the findings from the fixed effects model of the robustness test suggest that firms with higher R&D investment intensity experience lower volatility in their stock returns. This corroborates the results obtained using the proxy RDII_1. Consequently, hypothesis 1, which posits that firms with higher R&D investment intensity will experience greater total stock return volatility, does not find support in the robustness test either. Furthermore, Hypothesis 1a,

which suggests that firms with higher R&D investment intensity experience higher total stock return volatility during the COVID-19 pandemic, is not supported as RDCOV does not exhibit statistical significance at any level. This finding contradicts the fixed-effects results for TSVOL in section 5.3.1.2, where a weak significance at the 10% level is observed. Nonetheless, it is interesting to note that a similar trend is observed for RDCOV in the robustness test.

5.4.2 Robustness test Fixed effects model (IVOL)

The results of the robustness test are presented in Table 6, examining the impact of R&D investment intensity (RDII_2) on idiosyncratic volatility (IVOL). In the fixed-effects model (2), the findings reveal a weak negative statistical significance for the independent variable RDII_2 at a 10% level (-0.206, p-value < 0.10). This implies that a 1 unit increase in RDII_2 corresponds to a 0.206 decrease in idiosyncratic volatility. The standard deviation of RDII_2 is 0.116. Multiplying this value by -0.206 results in -0.023896. Therefore, the new total volatility would be approximately 2.39% lower than the previous level of total stock return volatility. These findings suggest that a higher level of R&D investment is associated with a reduction in idiosyncratic volatility, thereby failing to support hypothesis 2.

Additionally, the results reveal that RDCOV is statistically insignificant. Consequently, the analysis does not support hypothesis 2a, which suggests that firms with higher R&D investment intensity would experience greater idiosyncratic volatility during the COVID-19 pandemic. This finding is in line with the results obtained from the FE model in section 5.3.2.1. Furthermore, within the fixed effects model, the variable SIZE emerges as the only statistically significant factor. This finding suggests that larger firms tend to have lower levels of idiosyncratic volatility.

Table 6. Robustness test: effects of R&D investment intensity on the idiosyncratic volatility (IVOL)

VARIABLES	(1) Pooled	(2) FE	(3) RE
RDII_2	0.0991**	-0.206*	0.0300
	(0.0472)	(0.107)	(0.0631)
LVRG	0.0285	0.0532	0.0328
	(0.0239)	(0.0588)	(0.0352)
SIZE	-0.0768***	-0.131***	-0.0787***
	(0.00676)	(0.0431)	(0.0104)
AGE	-0.00101***	-0.00128	-0.00106***
	(0.000221)	(0.00495)	(0.000286)
COVID	0.100***	0.0970***	0.0951***
	(0.0165)	(0.0239)	(0.0159)
RDCOV	0.125	0.171	0.155
	(0.0872)	(0.114)	(0.106)
Constant	0.852***	1.151***	0.870***
	(0.0324)	(0.213)	(0.0513)
Observations	1,446	1,446	1,446
R-squared	0.194	0.068	
Number of B		220	220

Notes: This table presents the results of the robustness test aimed at investigating the relationship between idiosyncratic volatility (IVOL) and R&D investment intensity (RDII_2), and several control variables. TSVOL is the dependent variable, while RDII_2 is the independent variable. The control variables include LVRG, SIZE, AGE, and COVID, while RDCOV is the interaction term that captures the differential effects of R&D investments on stock return volatility during and post-COVID-19. Number of B refers to the number of unique firm-level clusters in the fixed effects regression. Standard errors are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1.

5.4.3 Robustness test LN(TSVOL) and LN(IVOL)

After conducting regression analyses using the natural logarithm of the variables TSVOL and IVOL, the results in Table A19 indicate that the independent variable R&D investment intensity (RDII_1) is not statistically significant for LN(TSVOL). However, it is worth noting that a negative relationship between RDII_1 and LN(TSVOL) is observed, consistent with the findings of our previous regression (TSVOL). Nevertheless, this relationship is statistically insignificant. The interaction term RDCOV also fails to demonstrate any statistical significance for LN(TSVOL), in contrast to our findings in the previous regression model. Consequently, when considering LN(TSVOL) as the dependent variable, hypotheses 1 and 1a are not supported, indicating that RDII_1 does not possess explanatory power for total stock return volatility when controlling for the variables LVRG, SIZE, and AGE.

On the other hand, the results in Table A20 indicate that when using the natural logarithm of IVOL as the dependent variable, RDII_1 is not statistically significant at any level. This finding holds true for the interaction term RDCOV as well. These results align with our previous regression analysis, confirming the robustness of the findings obtained in section 5.3.2.

Specifically, RDII_1 does not exhibit any explanatory power for idiosyncratic volatility when accounting for the variables LVRG, SIZE, and AGE.

Conclusion and discussion

This research aimed to determine the relationship between a firm's R&D investments and stock return volatility in the European biotechnology and pharmaceutical industry. The study filled a gap in the literature by focusing on European settings, which have been less explored compared to the United States. The research also investigated the impact of R&D investment on stock return volatility during the COVID-19 pandemic.

The results of the panel data regression analysis revealed that higher R&D investment levels had a significant effect on reducing total stock return volatility, contrary to hypothesis 1. This finding contradicts the expectation that firms with higher R&D investment intensity would experience greater stock return volatility. However, during the COVID-19 pandemic period, the interaction term RDCOV showed a weak positive effect on total stock return volatility. This implies that while firms with higher R&D investment intensity generally experienced lower volatility, they faced increased volatility in their total stock returns specifically during the pandemic. This result aligns with previous studies that documented higher market volatility and lower investor confidence during the pandemic (Bora et al., 2021; Liu et al., 2020).

Overall, these findings suggest that R&D investments can have both stabilizing and destabilizing effects on total stock return volatility, depending on the prevailing economic conditions. The resilience demonstrated by pharmaceutical and biotechnology firms during the COVID-19 pandemic likely contributed to increased investor confidence and reduced vulnerability to idiosyncratic shocks. Financial support provided by governments worldwide, along with greater access to critical information about R&D activities, may have stabilized stock prices and reduced information asymmetry.

Furthermore, when it comes to idiosyncratic volatility, the study found no evidence of a positive relationship with R&D investment intensity. This finding contrasts with the results of Gharbi et al. (2014), who reported a positive relationship between idiosyncratic volatility and R&D intensity. Moreover, the analysis revealed that the interaction term RDCOV was statistically insignificant in relation to idiosyncratic volatility. As a result, the analysis does not

support hypothesis 2a, which proposes that firms with higher R&D investment intensity experience higher idiosyncratic volatility during the COVID-19 pandemic. The accuracy of the results has been confirmed by the robustness tests.

In sum, conducting an analysis of the relationship between R&D investment intensity and stock return volatility in the biotechnology and pharmaceutical industry during the COVID-19 pandemic can provide valuable insights into the resilience and performance of firms in the face of unprecedented challenges. These insights have the potential to inform investment decisions and enhance risk management practices, enabling stakeholders to navigate uncertain times more effectively. By understanding how R&D investment intensity impacts stock return volatility, investors and policymakers, can make more informed decisions and strategies to mitigate risks and maximize opportunities in the dynamic market environment. This knowledge is important for promoting steady growth and stability in the biotechnology and pharmaceutical industry, especially during times of major disruptions like the COVID-19 pandemic. Lastly, the findings of this study suggest that pharmaceutical and biotechnological firms can potentially decrease the level of volatility in their stock returns by investing in R&D activities. This finding aligns with signaling theory, which proposes that firms use signals, such as R&D investments, to convey information about their quality and future prospects to the market. In this context, firms with higher R&D investment intensity may signal their commitment to innovation and growth, potentially influencing stock return volatility.

Limitations and recommendations

While this paper provides valuable insights into the relationship between R&D investment intensity and its impact on stock return volatility, there are certain limitations that should be acknowledged. These limitations open up possibilities for future research and suggest possible improvements to enhance our understanding of R&D activities and stock return.

First, there are various methods to measure R&D intensity. In this study, R&D intensity is measured as the ratio of R&D expenses to sales (Gharbi et al., 2014), which focuses on the input aspect of R&D investments, i.e., the resources allocated to R&D. However, it is important to note that there are also output-based measures for R&D, such as patents. Patents can be used to assess the number of patents granted to a firm or the number of citations received. A higher number of patents and citations can indicate a greater level of innovation and technological

advancement, suggesting that the firm's R&D activities are generating valuable intellectual property and contributing to the development of new technologies. Such positive outcomes can influence stock returns by attracting investor attention, fostering market confidence, and potentially leading to commercial success. On the other hand, low patent counts or limited citations may suggest lower levels of innovation or less impact from R&D investments, which can potentially contribute to higher stock return volatility as investors assess the risks and uncertainties associated with the firm's future prospects. In future research, it would be valuable to use both input and output measures of R&D intensity. By looking at the resources invested in R&D and the patents or citations obtained, researchers can get a better understanding of how R&D investments impacts the potential risks and returns for investors.

Additionally, in this study we did not consider government financial support as a control variable when analyzing the between R&D investment and stock return volatility in the context of the COVID-19 pandemic. During this challenging period, governments worldwide implemented a range of support measures, such as grants, subsidies, tax incentives, and direct funding, to aid businesses and industries, particularly in the biotechnology and pharmaceutical sectors. By providing financial assistance and tax benefits, these measures alleviate the financial burden on firms engaged in R&D. As a result, firms are able to free up more resources and funds, allowing them to allocate a greater amount of money towards their R&D projects. Therefore, to enhance future research, it would be beneficial to include government financial support as a control variable. This would enable a more comprehensive assessment of the potential impact of these external factors on R&D activities and stock market performance.

Moreover, our study solely focusses on the biotechnological and pharmaceutical industry. Based on our findings, we are certain that industry has made significant investments in R&D and demonstrated resilience during the COVID-19 pandemic. It would be interesting to compare these findings with other industries that also invest heavily in R&D, like the high-tech sector, during the same period. By conducting this comparative analysis, we can examine if similar patterns and outcomes emerge in different industries. This analysis would offer valuable insights into the broader applicability and reliability of our observed results, specifically in relation to the challenges presented by the COVID-19 pandemic. It would help us understand if the trends and outcomes we observed in the biotechnological and pharmaceutical industry hold true across various sectors, shedding light on the generalizability and robustness of our findings.

Appendices

Figure A1. Scatter of Linearity between variables (dependent variable: TSVOL)

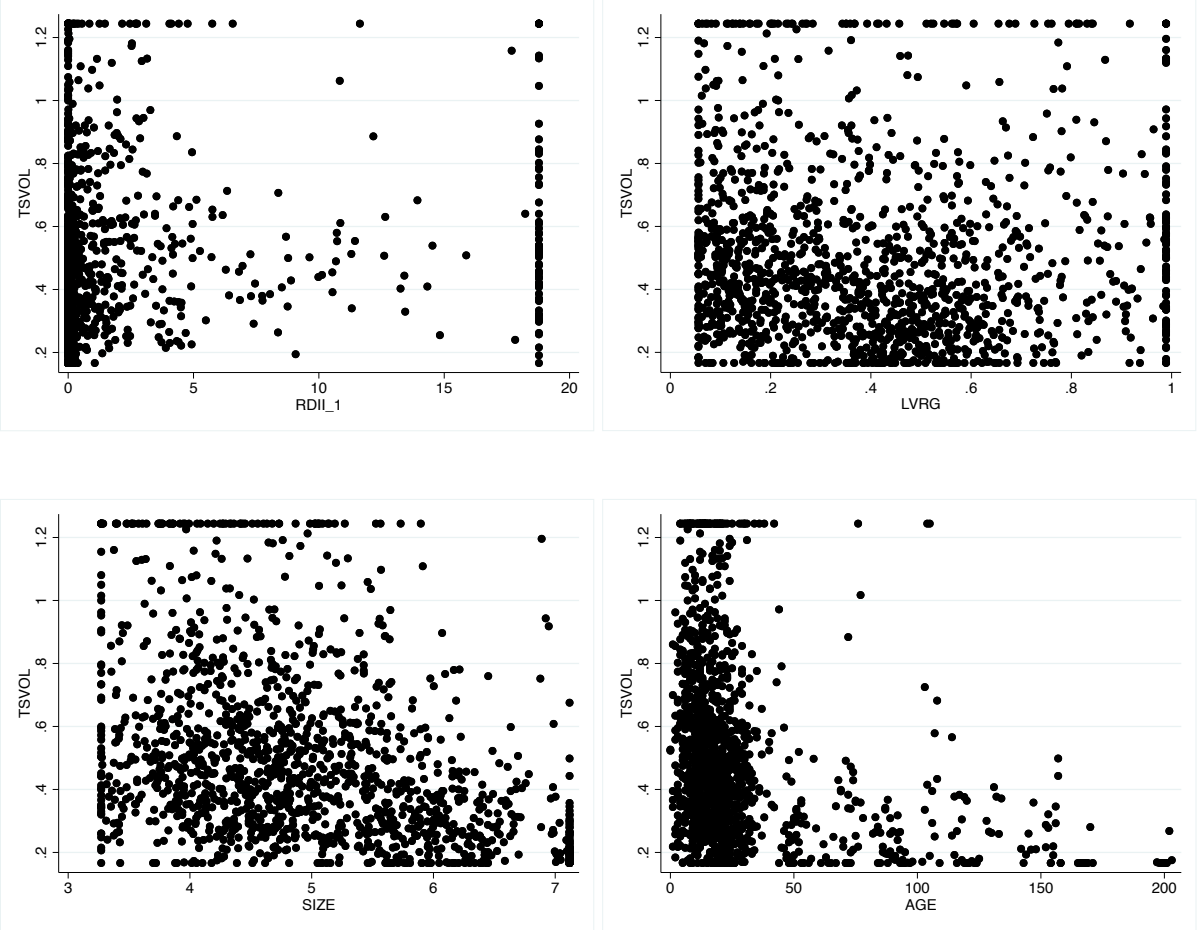

Figure A2. Scatter of Linearity between variables (dependent variable: IVOL)

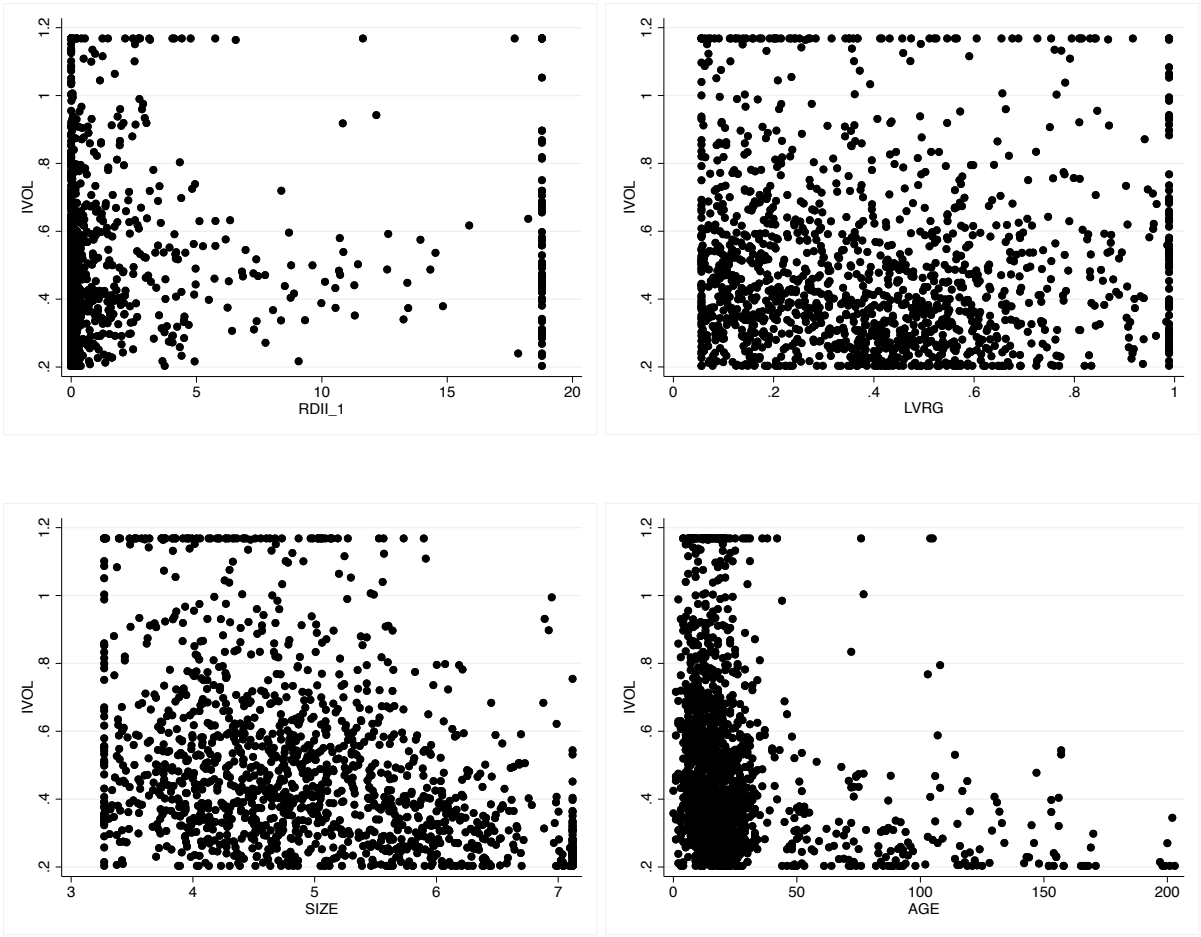

Figure A3. Histogram of Residual Distribution

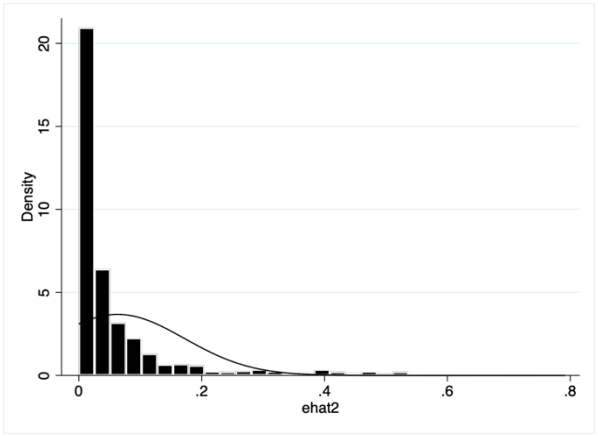

Table A1. Descriptive Statistics of Variables pre-COVID period

Variable	N	Mean	SD	Min	Max
TSVOL	1010	.471	.262	.166	1.244
IVOL	1013	.47	.239	.203	1.168
RDII 1	991	1.976	4.68	0	18.778
RDII 2	1100	0.119	0.159	0	0.542
LVRG	1100	.391	.263	.056	.989
SIZE	1100	4.844	1.043	3.271	7.118
AGE	1100	25.305	31.009	0	201

Notes: This table presents the summary statistics of the variables used in this research during the pre-COVID period (2015-2019). All variables, except for "age," have been winsorized at the 5% level. Variable definitions are described in Table 1.

Table A2. Descriptive Statistics of Variables during COVID period

Variable	N	Mean	SD	Min	Max
TSVOL	433	.568	.315	.166	1.244
IVOL	433	.576	.286	.203	1.168
RDII 1	397	1.534	4.076	0	18.778
RDII 2	440	0.109	0.151	0	0.542
LVRG	440	.418	.27	.056	.989
SIZE	440	4.997	1.041	3.271	7.118
AGE	440	28.805	31.002	5	203
COVID	440	1	0	1	1

Notes: This table presents the summary statistics of the variables used in this research during the COVID period (2020 – 2021). All variables, except for "age," have been winsorized at the 5% level. Variable definitions are described in Table 1.

Table A3. Wooldridge test for autocorrelation in panel data for TSVOL

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
F(1, 197) = 6.999
Prob > F = 0.0088

Note: The reported test statistic value of 6.999 and the associated p-value of 0.0088 indicate that the test statistic is statistically significant at the 0.05 level of significance. Therefore, there is evidence to reject the null hypothesis and conclude that there is first-order autocorrelation present in the regression model.

Table A4. Wooldridge test for autocorrelation in panel data for IVOL

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
F(1, 197) = 4.697
Prob > F = 0.0314

Note: The reported test statistic value of 4.697 and the associated p-value of 0.0314 indicate that the test statistic is statistically significant at the 0.05 level of significance. Therefore, there is evidence to reject the null hypothesis and conclude that there is first-order autocorrelation present in the regression model.

Table A5. Heteroskedasticity- White's Test for TSVOL

Source	SS	df	MS
Model	21.1553226	6	3.5258871
Residual	81.34197	1.310	.062093107
Total	102.497293	1.316	.077885481

Number of obs	=	1.317
F (6, 1313)	=	56.78
Prob > F	=	0.0000
R-squared	=	0.2064
Adj R-squared	=	0.2028
Root MSE	=	.24918

TSVOL	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
RDII_1	.0049845	.0017899	2.78	0.005	.001473	.0084959
LVRG	.0811179	.0272123	2.98	0.003	.0277334	.1345025
SIZE	-.0889582	.0074339	-11.97	0.000	-.1035419	-.0743746
AGE	-.0011042	.0002384	-4.63	0.000	-.0015719	-.0006364
COVID	.1022998	.0161409	6.34	0.000	.0706349	.1339648
(c.RDII_1#c.COVID	.0040664	.003547	1.15	0.252	-.002892	.0110248
_cons	.889517	.0359529	24.74	0.000	.8189854	.9600486

White's test
H0: Homoskedasticity
Ha: Unrestricted heteroskedasticity

chi2(23) = 102.43
Prob > chi2 = 0.0000

Cameron & Trivedi's decomposition of IM-test

Source	chi2	df	p
Heteroskedasticit	102.43	23	0.0000
y	151.98	6	0.0000
Skewness			
Residual	46.57	1	0.0000
Total	300.98	30	0.0000

Table A6. Heteroskedasticity- White's Test for IVOL

Source	SS	df	MS
Model	16.5498411	6	2.75830685
Residual	68.6672472	1.313	.05229798
Total	85.2170883	1.319	.064607345

Number of obs	=	1.320
F (6, 1313)	=	52.74
Prob > F	=	0.0000
R-squared	=	0.1942
Adj R-squared	=	0.1905
Root MSE	=	.22869

IVOL	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
RDII_1	.0037384	.0016396	2.28	0.023	.000522	.0069549
LVRG	.0621072	.0249485	2.49	0.013	.013164	.1110504
SIZE	-.075488	.0068207	-11.07	0.000	-.0888687	-.0621073
AGE	-.0009749	.0002188	-4.46	0.000	-.0014041	-.0005457
COVID	.1065095	.0148117	7.19	0.000	.0774523	.1355668
(c.RDII_1#c.COVID	.0046518	.0032535	1.43	0.153	-.0017309	.0110345
_cons	.8298456	.0329954	25.15	0.000	.7651161	.8945751

White's test
H0: Homoskedasticity
Ha: Unrestricted heteroskedasticity

chi2(23) = 107.64
Prob > chi2 = 0.0000

Cameron & Trivedi's decomposition of IM-test

Source	chi2	df	p
Heteroskedasticity	107.87	23	0.0000
Skewness	163.58	6	0.0000
Residual	47.05	1	0.0000
Total	318.50	30	0.0000

Table A7. VIF Test TSVOL

Variable	VIF	1/VIF
RDII_1	1.39	0.720339
LVRG	1.06	0.945396
SIZE	1.29	0.778179
AGE	1.27	0.784862
COVID	1.15	0.866929
c.RDII_1# c.COVID	1.47	0.682466
Mean VIF	1.27	

Note: VIF is 1.27. A value between 1 and 5 indicates moderate correlation between a given explanatory variable and other explanatory variables in the model, but this is often not severe enough to require attention.

Table A8. VIF Test IVOL

Variable	VIF	1/VIF
RDII_1	1.39	0.720270
LVRG	1.06	0.944648
SIZE	1.28	0.778550
AGE	1.27	0.784648
COVID	1.15	0.866273
c.RDII_1# c.COVID	1.46	0.683117
Mean VIF	1.27	

Note: VIF is 1.27. A value between 1 and 5 indicates moderate correlation between a given explanatory variable and other explanatory variables in the model, but this is often not severe enough to require attention.

Table A9. Random-effects model TSVOL

Random-effects GLS regression		Number of obs	= 1.317
Group variable: B		Number of groups	= 212
R-squared:		Obs per group:	
Within	= 0.0493	min	= 1
Between	= 0.3783	avg	= 6.2
Overall	= 0.2038	max	= 7
corr(u_i, X) = 0 (assumed)		Wald chi2(6)	= 183.76
		Prob > chi2	= 0.0000

IVOL	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
RDII_1	.0017801	.0020588	0.86	0.387	-.002255	.0058153
LVRG	.0602235	.0340883	1.77	0.077	-.0065884	.1270353
SIZE	-.0924775	.0112544	-8.22	0.000	-.1145358	-.0704193
AGE	-.0012097	.0003776	-3.20	0.001	-.0019498	-.0004697
COVID	.0999896	.0145361	6.88	0.000	.0714994	.1284798
RDCOV	.004988	.003314	1.51	0.132	-.0015073	.0114832
_cons	.9304579	.0538894	17.27	0.000	.8248367	1.036079
sigma_u	.12773552					
sigma_e	.2230857					
rho	.24690489	(fraction of variance due to u_i)				

Table A10. Random-effects model IVOL

Random-effects GLS regression		Number of obs	= 1.320
Group variable: B		Number of groups	= 212
R-squared:		Obs per group:	
Within	= 0.0601	min	= 1
Between	= 0.3657	avg	= 6.2
Overall	= 0.1922	max	= 7
corr(u_i, X) = 0 (assumed)		Wald chi2(6)	= 189.94
		Prob > chi2	= 0.0000

IVOL	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
RDII_1	.0011983	.001874	0.64	0.523	-.0024746	.0048713
LVRG	.0446086	.0308911	1.44	0.149	-.0159369	.105154
SIZE	-.0784162	.0100192	-7.83	0.000	-.0980535	-.0587789
AGE	-.001056	.0003346	-3.16	0.002	-.0017119	-.0004001
COVID	.1032657	.0134769	7.66	0.000	.0768515	.1296799
RDCOV	.005558	.0030661	1.81	0.070	-.0004515	.0115675
_cons	.8638545	.0480001	18.00	0.000	.7697761	.957933
sigma_u	.11051933					
sigma_e	.20700958					
rho	.22181005	(fraction of variance due to u_i)				

Table A11. Fixed-effects model TSVOL

Fixed-effects (within) regression		Number of obs	= 1.317
Group variable: B		Number of groups	= 212
R-squared:		Obs per group:	
Within	= 0.0556	min	= 1
Between	= 0.3119	avg	= 6.2
Overall	= 0.1688	max	= 7
corr(u_i, Xb) = -0.6551		F(6,1102)	= 10,78
		Prob > F	= 0.0000

IVOL	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
RDII_1	-.0046572	.002784	-1.67	0.095	-.0101197	.0008053
LVRG	.0160078	.0489381	0.33	0.744	-.0800148	.1120304
SIZE	-.1228472	.0368514	-3.33	0.001	-.1951542	-.0505402
AGE	-.0048831	.0053508	-0.91	0.362	-.0153821	.0056159
COVID	.1138618	.0229602	4.96	0.000	.068811	.1589127
RDCOV	.0062523	.0034618	1.81	0.071	-.0005402	.0130448
_cons	1.208067	.2141716	5.64	0.000	.7878356	1.628298
sigma_u	.16201081					
sigma_e	.20700958					
rho	.37984549	(fraction of variance due to u_i)				

F test that all u_i=0: F(211, 1099) = 2.54. Prob > F = 0.0000

Table A12. Fixed-effects model IVOL

Fixed-effects (within) regression		Number of obs	= 1.320
Group variable: B		Number of groups	= 212
R-squared:		Obs per group:	
Within	= 0.0653	min	= 1
Between	= 0.3220	avg	= 6.2
Overall	= 0.1718	max	= 7
corr(u_i, X) = 0 (assumed)		F(6,1102)	= 12,82
		Prob > F	= 0.0000

IVOL	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
RDII_1	-.0041331	.0025804	-1.60	0.109	-.0091961	.0009299
LVRG	.001018	.0453012	0.02	0.982	-.0878684	.0899045
SIZE	-.1117552	.0341772	-3.27	0.001	-.1788148	-.0446955
AGE	-.0025727	.0049568	-0.52	0.604	-.0122986	.0071532
COVID	.1093137	.021295	5.13	0.000	.0675304	.151097
RDCOV	.0067517	.0032119	2.10	0.036	.0004496	.0130537
_cons	1.095.573	.1986041	5.52	0.000	.7058881	1.485.258
sigma_u	.16201081					
sigma_e	.20700958					
rho	.37984549	(fraction of variance due to u_i)				

F test that all u_i=0: F(211, 1102) = 2.37. Prob > F = 0.0000

Table A13. Hausman Test TSVOL

	— Coefficients —			
	(b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
RDII_1	-.0046572	.0017801	-.0064373	.0018491
LVRG	.0160078	.0602235	-.0442157	.034703
SIZE	-.1228472	-.0924775	-.0303697	.0348588
AGE	-.0048831	-.0012097	-.0036734	.0053053
COVID	.1138618	.0999896	.0138722	.0175947
RDCOV	.0062523	.004988	.0012644	.0009266

b = Consistent under H0 and Ha; obtained from xtreg.
B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

chi2(6) = (b-B)'[(V_b-V_B) ^ (-1)] (b-B)
= 15.07
Prob > chi2 = 0.0197

Table A14. Hausman Test IVOL

	— Coefficients —			
	(b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
RDII_1	-.0041331	.0011983	-.0053314	.0017519
LVRG	.001018	.0446086	-.0435905	.0327735
SIZE	-.1117552	-.0784162	-.033339	.0324673
AGE	-.0025727	-.001056	-.0015167	.0049166
COVID	.1093137	.1032657	.006048	.0163274
RDCOV	.0067517	.005558	.0011937	.0008916

b = Consistent under H0 and Ha; obtained from xtreg.
B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

chi2(6) = (b-B)'[(V_b-V_B) ^ (-1)] (b-B)
= 14.19
Prob > chi2 = 0.0276

Note: Ho= RE and Ha= FE We reject H0 so Fixed effects model is preferred.

Table A15. Breusch and Pagan Lagrangian multiplier test for random effects (TSVOL)

	Var	SD = sqrt(Var)
TSVOL	.0778855	.2790797
e	.0497672	.2230857
u	.0163164	.1277355

Note: Ho= Presence of random effects, data is Poolable and Ha= Data is not poolable Breusch and Pagan Lagrangian multiplier test for random effects. We reject Ho meaning the data is not poolable. Thus, Hausman and BP test strongly prefer a Fixed effects model

Test: Var(u) = 0
chibar2(01) = 105.14
Prob > chibar2 = 0.0000

Table A16. Breusch and Pagan Lagrangian multiplier test for random effects (IVOL)

	Var	SD = sqrt(Var)
IVOL	.0646073	.2541797
e	.042853	.2070096
u	.0122145	.1105193

Note: Ho= Presence of random effects, data is Poolable and Ha= Data is not poolable
We reject Ho meaning the data is not poolable.

Test: Var(u) = 0
chibar2(01) = 88.85
Prob > chibar2 = 0.0000

Table A17. Sample

Company name	ISO Code	NACE Rev. 2
BONE THERAPEUTICS SA	BE	2120
CELYAD ONCOLOGY SA	BE	2120
GALAPAGOS NV	BE	7211
MDXHEALTH SA	BE	2120
MITHRA PHARMACEUTICALS SA	BE	2120
OXURION NV	BE	2120
SOLVAY SA	BE	2120
UCB S.A	BE	2120
ADDEX THERAPEUTICS SA	CH	2120
BACHEM HOLDING AG	CH	2120
BASILEA PHARMACEUTICA AG	CH	2120
DOTTIKON ES HOLDING AG	CH	2120
EVOLVA HOLDING AG	CH	2120
KUROS BIOSCIENCES AG	CH	2120
MOLECULAR PARTNERS AG	CH	2120
NOVARTIS AG	CH	2120
ROCHE HOLDING AG	CH	2120
SANTHERA PHARMACEUTICALS HOLDING LTD	CH	2120
SIEGFRIED HOLDING AG	CH	2120
4SC AG	DE	2120
B.M.P. PHARMA TRADING AG	DE	2120
BAYER AG	DE	2120
BIOFRONTERA AG	DE	2120
EPIGENOMICS AG	DE	2120
EVOTEC SE	DE	2120
HEIDELBERG PHARMA AG	DE	2120
MAGFORCE AG	DE	2120
MEDIGENE AG	DE	2120
MERCK KOMMANDITGESELLSCHAFT AUF AKTIEN	DE	2120
MORPHOSYS AG	DE	7211
PAION AG	DE	2120
PAUL HARTMANN AG	DE	2120
VERBIO VEREINIGTE BIOENERGIE AG	DE	2120
VITA 34 AG	DE	2120
ALK-ABELLO A/S	DK	2120
ASCENDIS PHARMA A/S	DK	7211
BAVARIAN NORDIC A/S	DK	2120
FORWARD PHARMA A/S	DK	2120
GENMAB A/S	DK	7211
H. LUNDBECK A/S	DK	2120
NOVO NORDISK A/S	DK	2120
NOVOZYMES A/S	DK	2110
PHOTOCAT A/S	DK	7220
ZEALAND PHARMA A/S	DK	7211
ADL BIONATUR SOLUTIONS, S.A.	ES	2120
FAES FARMA S.A.	ES	2120
GRIFOLS S.A.	ES	2120
PHARMA MAR S.A.	ES	2120
FARON PHARMACEUTICALS OY	FI	2120
HERANTIS PHARMA OYJ	FI	7211
ORION OYJ	FI	2120
AB SCIENCE	FR	2120
ABIONYX PHARMA	FR	2120
ADOCIA	FR	2120
BIOMERIEUX SA	FR	2120
BIOPHYTIS	FR	7211
BOIRON	FR	2110
CELLECTIS	FR	7211
ERYTECH PHARMA	FR	2120
EUROBIO SCIENTIFIC	FR	7211
GENFIT	FR	7211
GENOMIC VISION	FR	2120
GENSIGHT BIOLOGICS	FR	2120
GLOBAL BIOENERGIES	FR	2120
GUERBET	FR	2120
INNATE PHARMA	FR	7211
INVENTIVA	FR	2120
IPSEN	FR	2120
LYSOGENE	FR	2120
NANOBIOTIX	FR	2120
NEOVACS	FR	2120
NICOX SA	FR	2110
ONXEO	FR	2120
OSE IMMUNOTHERAPEUTICS	FR	7211
POXEL	FR	2120
QUANTUM GENOMICS	FR	2120
SANOFI	FR	2120
SENSORION	FR	2120
VALNEVA	FR	2120
VETOQUINOL S A	FR	2120
ABCAM PLC	GB	2120
ADAPTIMMUNE THERAPEUTICS PLC	GB	7211
AKARI THERAPEUTICS PLC	GB	2120

Company name	ISO Code	NACE Rev. 2
ALLERGY THERAPEUTICS PLC	GB	2120
AMARIN CORPORATION PLC	GB	2120
ASTRAZENECA PLC	GB	2120
AVACTA GROUP PLC	GB	2120
BENCHMARK HOLDINGS PLC	GB	2120
C4X DISCOVERY HOLDINGS PLC	GB	2120
CAMBRIDGE COGNITION HOLDINGS PLC	GB	2120
CIRCASSIA GROUP PLC	GB	2120
DECHRA PHARMACEUTICALS PLC	GB	2120
DESTINY PHARMA PLC	GB	2120
DIURNAL GROUP PLC	GB	2120
EDEN RESEARCH PLC	GB	2120
ERGOMED PLC	GB	2120
E-THERAPEUTICS PLC	GB	7211
EVGEN PHARMA PLC	GB	2120
FUTURA MEDICAL PLC	GB	2120
GENEDRIVE PLC	GB	7211
GENUS PLC	GB	7211
GSK PLC	GB	2120
HIKMA PHARMACEUTICALS PLC	GB	2120
INDIVIOR PLC	GB	2120
IXICO PLC	GB	2110
MIDATECH PHARMA PLC	GB	7211
NANOCO GROUP PLC	GB	7211
NETSCIENTIFIC PLC	GB	2120
OPTIBIOTIX HEALTH PLC	GB	7220
OXFORD BIODYNAMICS PLC	GB	2120
OXFORD BIOMEDICA PLC	GB	2120
PHYSIOMICS PLC	GB	2120
PROTEOME SCIENCES PLC	GB	2120
QUOTIENT LIMITED	GB	2120
REDX PHARMA PLC	GB	2120
RENEURON GROUP PLC	GB	2120
SAREUM HOLDINGS PLC	GB	2120
SCANCELL HOLDINGS PLC	GB	2120
SHIELD THERAPEUTICS PLC	GB	2120
SYNAIRGEN PLC	GB	2120
TISSUE REGENIX GROUP PLC	GB	2120
VERONA PHARMA PLC	GB	7211
LAVIPHARM S.A.	GR	2120
NUTEX BEFEKTETESI NYRT.	HU	2120
RICHTER GEDEON VEGYESZETI GYAR RT	HU	2120
ALKERMES PUBLIC LIMITED COMPANY	IE	2120
AVADEL PHARMACEUTICALS PLC	IE	2120
ENDO INTERNATIONAL PLC	IE	2120
HORIZON PHARMA PUBLIC LIMITED COMPANY	IE	2120
JAZZ PHARMACEUTICALS PUBLIC LIMITED COMPANY	IE	2120
NABRIVA THERAPEUTICS PLC	IE	7211
PERRIGO CO PLC	IE	2120
PROTHENA CORPORATION PLC	IE	2120
TRINITY BIOTECH PLC	IE	2120
DIASORIN S.P.A.	IT	2120
NEWRON PHARMACEUTICALS SPA	IT	2120
AFFIMED N.V.	NL	7211
AKZO NOBEL NV	NL	2120
ARGENX SE	NL	7211
MERUS N.V.	NL	7211
PHARMING GROUP NV	NL	2120
PROQR THERAPEUTICS N.V.	NL	7211
UNIQURE N.V.	NL	7211
AQUA BIO TECHNOLOGY ASA	NO	2120
HOFSETH BIOCARE ASA	NO	2120
NORDIC NANOVECTOR ASA	NO	2120
PCI BIOTECH HOLDING ASA	NO	2120
PHOTOCURE ASA	NO	2120
BIOTON S.A.	PL	2120
GENOMED SA	PL	7211
HEMP & HEALTH SA	PL	2120
INNO-GENE SA	PL	7211
LABOCANNA SA	PL	2110
MABION SA	PL	2120
PHARMENA S.A.	PL	2120
YELLOW BOSON SA	PL	7220
CEPROHART SA BRAILA	RO	7211
S.C. CEPROCIM SA	RO	7211
SINTOFARM SA BUCURESTI	RO	2120
ACOUSORT AB	SE	7220
ALLIGATOR BIOSCIENCE AB	SE	7220
ALTECO MEDICAL AB	SE	2120
ALZINOVA AB	SE	2120
APTAHEM AB	SE	2110
ATTANA AB	SE	2120
BIOINVENT INTERNATIONAL AB	SE	2110

Company name	ISO Code	NACE Rev. 2
BIOTAGE AB	SE	7211
BRAIN COOL AB	SE	7211
BRIGHTER AB	SE	2120
CAMURUS AB	SE	7211
CANTARGIA AB	SE	2120
CERENO SCIENTIFIC AB	SE	2120
CLINE SCIENTIFIC AB	SE	7211
CLINICAL LASERTHERMIA SYSTEMS AB	SE	2120
CORLINE BIOMEDICAL AB	SE	7220
DEXTECH MEDICAL AB	SE	7211
EGETIS THERAPEUTICS AB	SE	7211
ENORAMA PHARMA AB	SE	2120
EUROCINE VACCINES AB	SE	2120
EUROPEAN INSTITUTE OF SCIENCE AB	SE	7211
HANSA BIOPHARMA AB	SE	2120
IDOGEN AB	SE	2120
INFANT BACTERIAL THERAPEUTICS AB	SE	2120
KANCERA AB	SE	2120
KAROLINSKA DEVELOPMENT AB	SE	7211
KLARIA PHARMA HOLDING AB	SE	7220
KONTIGO CARE AB	SE	7211
LIDDS AB	SE	2120
MEDIVIR AB	SE	2120
MENDUS AB	SE	2120
MOBERG PHARMA AB	SE	2120
NICOCCINO HOLDING AB	SE	2110
NOVUS GROUP INTERNATIONAL AB	SE	7220
OASMIA PHARMACEUTICAL AB	SE	2120
PEPTONIC MEDICAL AB	SE	2110
PHARMACOLOG I UPPSALA AB	SE	7220
PHARMALUNDENSIS AB	SE	2120
PREBONA AB	SE	7211
PROBI AB	SE	7211
PROSTALUND AB	SE	7211
SPAGO NANOMEDICAL AB	SE	2120
SPRINT BIOSCIENCE AB	SE	2120
SWEDISH ORPHAN BIOVITRUM AB	SE	2120
XBRANE BIOPHARMA AB	SE	2120
KRKA DD NOVO MESTO	SI	2120
GEOCOMPLEX A.S.	SK	7211

Table A18. Average risk-free rate per year for each European country

Average risk-free rate per year for each European country (in research sample)								
	ISO CODE	**2021**	**2020**	**2019**	**2018**	**2017**	**2016**	**2015**
Belgium	BE	-0,01	-0,15	0,19	0,80	0,72	0,48	0,84
Switzerland	CH	-0,23	-0,52	-0,49	0,03	-0,07	-0,36	-0,07
Germany	DE	-0,37	-0,51	-0,25	0,40	0,32	0,09	0,50
Denmark	DK	-0,06	-0,36	-0,18	0,45	0,48	0,32	0,69
Spain	ES	0,35	0,38	0,66	1,42	1,56	1,39	1,73
Finland	FI	-0,09	-0,22	0,07	0,66	0,55	0,37	0,72
France	FR	0,01	-0,15	0,13	0,78	0,81	0,47	0,84
Great Britain	GB	0,79	0,37	0,94	1,46	1,24	1,31	1,90
Hungary	HU	3,06	2,23	2,47	3,06	2,96	3,14	3,43
Ireland	IE	0,06	-0,06	0,33	0,95	0,80	0,74	1,18
Italy	IT	0,81	1,17	1,95	2,61	2,11	1,49	1,71
Netherlands	NL	-0,33	-0,38	-0,07	0,58	0,52	0,29	0,69
Norway	NO	1,40	0,82	1,49	1,88	1,64	1,33	1,56
Poland	PL	1,95	1,50	2,35	3,20	3,42	3,04	2,70
Romania	RO	3,63	3,89	4,54	4,69	3,96	3,32	3,47
Sweden	SE	0,27	-0,04	0,04	0,65	0,65	0,54	0,72
Slovenia	SI	0,07	0,08	0,28	0,93	0,96	1,15	1,71
Slovakia	SK	-0,08	-0,04	0,25	0,89	0,92	0,54	0,89

Table A19. Robustness test: Regression Results with Natural Logarithm of TSVOL

VARIABLES	(1) lnPooled	(2) lnFE	(3) lnRE
RDII_1	0.0115***	-0.00613	0.00518
	(0.00333)	(0.00706)	(0.00482)
LVRG	0.150***	0.0438	0.0990
	(0.0506)	(0.112)	(0.0771)
SIZE	-0.188***	-0.147	-0.185***
	(0.0138)	(0.0895)	(0.0248)
AGE	-0.00319***	-0.0168*	-0.00352***
	(0.000444)	(0.00970)	(0.000741)
COVID	0.197***	0.233***	0.196***
	(0.0300)	(0.0436)	(0.0274)
RDCOV	0.00309	0.00548	0.00382
	(0.00660)	(0.00738)	(0.00735)
Constant	0.0206	0.274	0.0589
	(0.0669)	(0.478)	(0.113)
Observations	1,317	1,317	1,317
R-squared	0.270	0.051	
Number of B		212	212

Notes: This table presents the results of the robustness test aimed at investigating the relationship between total stock return volatility (TSVOL) and R&D investment intensity (RDII_1), and several control variables. The natural logarithm of TSVOL (LN(TSVOL)) is utilized as the dependent variable, while RDII_2 is the independent variable. The control variables include LVRG, SIZE, AGE, and COVID, while RDCOV is the interaction term that captures the differential effects of R&D investments on stock return volatility during and post-COVID-19. Number of B refers to the number of unique firm-level clusters in the fixed effects regression. Standard errors are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A19. Robustness test: Regression Results with Natural Logarithm of IVOL

VARIABLES	(1) lnPooled	(2) lnFE	(3) lnRE
RDII_1	0.00864***	-0.00564	0.00403
	(0.00299)	(0.00610)	(0.00399)
LVRG	0.108**	0.00943	0.0728
	(0.0455)	(0.0992)	(0.0670)
SIZE	-0.151***	-0.138*	-0.151***
	(0.0124)	(0.0817)	(0.0201)
AGE	-0.00258***	-0.00602	-0.00280***
	(0.000399)	(0.00909)	(0.000614)
COVID	0.207***	0.207***	0.203***
	(0.0270)	(0.0402)	(0.0235)
RDCOV	0.00378	0.00668	0.00480
	(0.00593)	(0.00653)	(0.00650)
Constant	-0.124**	-0.0251	-0.0879
	(0.0602)	(0.438)	(0.0932)
Observations	1,320	1,320	1,320
R-squared	0.240	0.061	
Number of B		212	212

Notes: This table presents the results of the robustness test aimed at investigating the relationship between total stock return volatility (IVOL) and R&D investment intensity (RDII_1), and several control variables. The natural logarithm of IVOL (LN(IVOL)) is utilized as the dependent variable, while RDII_2 is the independent variable. The control variables include LVRG, SIZE, AGE, and COVID, while RDCOV is the interaction term that captures the differential effects of R&D investments on stock return volatility during and post-COVID-19. Number of B refers to the number of unique firm-level clusters in the fixed effects regression. Standard errors are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Bibliography

Aboody, D., & Lev, B. (2000). Information Asymmetry, R&D, and Insider Gains. In *Source: The Journal of Finance* (Vol. 55, Issue 6).

Adrian, T., Rosenberg, J., Campbell, J., Diebold, F., Engle, R., Estrella, A., Ghysels, E., Schuermann, T., Sheppard, K., Wang, J., & Wang, Z. (2008). Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk. *The Journal of Finance*, *63*(6), 2997–3030. https://doi.org/10.1111/J.1540-6261.2008.01419.X

Agrawal, G., Hermann, R., Møller, M., Poetes, R., & Steinmann, M. (2021). *Fast-forward: Will the speed of COVID-19 vaccine development reset industry norms?* https://www.mckinsey.com/industries/life-sciences/our-insights/fast-forward-will-the-speed-of-covid-19-vaccine-development-reset-industry-norms

Amir, E., & Lev, B. (1996). Value-relevance of nonfinancial information: The wireless communications industry. *Journal of Accounting and Economics*, *22*(1–3), 3–30. https://doi.org/10.1016/S0165-4101(96)00430-2

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics*, 61(1), 43-76. https://doi.org/10.1016/S0304-405X(01)00055-1

Ang, J., & Cheng, Y. (2011). The Endogeneity of Information Asymmetry and Corporate Financing Decisions. *Journal of Financial Research*, *34*(3), 411–440. https://doi.org/10.1111/J.1475-6803.2011.01296.X

Ashraf, B. N. (2020). Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance*, *54*, 101249. https://doi.org/10.1016/J.RIBAF.2020.101249

Attanasio, O. P. (1990). Asset price volatility and information structures. *Economics Letters*, *33*(2), 159–164. https://doi.org/10.1016/0165-1765(90)90162-T

Baek, S., Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters*, *37*. https://doi.org/10.1016/J.FRL.2020.101748

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The Unprecedented Stock Market Reaction to COVID-19. *The Review of Asset Pricing Studies*, *10*(4), 742–758. https://doi.org/10.1093/RAPSTU/RAAA008

Bansal, R., Croce, M. M., Liao, W., & Rosen, S. (2016). Uncertainty-Induced Reallocations and the Macroeconomy. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2872105

Barker, V. L., & Mueller, G. C. (2002). CEO characteristics and firm R&D spending. *Management Science*, *48*(6), 782–801. https://doi.org/10.1287/MNSC.48.6.782.187

Barney, J. B. (2000). Firm resources and sustained competitive advantage. *Advances in Strategic Management*, *17*, 203–227. https://doi.org/10.1016/S0742-3322(00)17018-4/FULL/XML

Bell, A., Fairbrother, M., & Jones, K. (2019). Fixed and random effects models: making an informed choice. *Quality and Quantity*, *53*(2), 1051–1074. https://doi.org/10.1007/s11135-018-0802-x

Bhushan, R. (1989). Firm Characteristics and Analyst Following. *Journal of Accounting and Economics*, *11*, 255–274.

Bora, D., & Basistha, D. (2021). The outbreak of COVID-19 pandemic and its impact on stock market volatility: Evidence from a worst-affected economy. *Journal of Public Affairs*, *21*(4), e2623. https://doi.org/10.1002/PA.2623

Cameron, A. C., & Miller, D. L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Source: The Journal of Human Resources*, *50*(2), 317–372.

Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance*, *56*(1), 1–43. https://doi.org/10.1111/0022-1082.00318

Chan, L. K. C., Lakonishok, J., & Sougiannis, T. (2001). The stock market valuation of research and development expenditures. In *Journal of Finance* (Vol. 56, Issue 6, pp. 2431–2456). John Wiley & Sons, Ltd. https://doi.org/10.1111/0022-1082.00411

Chan, S. H., Martin, J. D., & Kensinger, J. W. (1990). Corporate research and development expenditures and share value. *Journal of Financial Economics*, *26*(2), 255–276. https://doi.org/10.1016/0304-405X(90)90005-K

Chen, W. R., & Miller, K. D. (2007). Situational and institutional determinants of firms' R&D search intensity. *Strategic Management Journal*, *28*(4), 369–381. https://doi.org/10.1002/SMJ.594

Cheung, W., Fung, S., & Tsai, S.-C. (2010). Global capital market interdependence and spillover effect of credit risk: evidence from the 2007–2009 global financial crisis. *Applied Financial Economics*, 20(1-2), 85–103. doi:10.1080/

Cohen, W. M., Nelson, R. R., & Walsh, J. P. (2000). Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not). *New York*, *7552*(7552), 50. https://doi.org/10.1093/dnares/dsr014

Cyert, R. M., & March, J. G. (1963). *A Behavioral Theory of the Firm*. https://papers.ssrn.com/abstract=1496208

Czarnitzki, D. (2006). Research and development in small and medium-sized enterprises: the role of financial constraints and public funding. *Scottish Journal of Political Economy*, *53*(3), 335–357. https://doi.org/10.1111/J.1467-9485.2006.00383.X

Dimasi, J. A., & Grabowski, H. G. (2007). The cost of biopharmaceutical R&D: Is biotech different? *Managerial and Decision Economics*, *28*(4–5), 469–479. https://doi.org/10.1002/mde.1360

Driver, C., & Guedes, M. J. C. (2012). Research and development, cash flow, agency and governance: UK large companies. *Research Policy*, *41*(9), 1565–1577. https://doi.org/10.1016/J.RESPOL.2012.04.003

Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *The Stata Journal*, 168–177. http://www.stata-journal.com

EFPIA - European Federation of Pharmaceutical Industries and Associations. (2019). The Pharmaceutical Industry in Figures. In *The Pharmaceutical Industry in Figures*. www.efpia.eu

Ehie, I. C., & Olibe, K. (2010). The effect of R&D investment on firm value: An examination of US manufacturing and service industries. *International Journal of Production Economics*, *128*(1), 127–135. https://doi.org/10.1016/j.ijpe.2010.06.005

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance*, *51*(1), 55–84. https://doi.org/10.1111/j.1540-6261.1996.tb05202.x

Ferreira, M. A., Laux, P. A., Larcker, D., Matos, P., Raposo, C., Schweitzer, R., & Yeung, B. (2007). Corporate Governance, Idiosyncratic Risk, and Information Flow. *The Journal of Finance*, *62*(2), 951–989. https://doi.org/10.1111/J.1540-6261.2007.01228.X

French, K. R., & Roll, R. (1986). Stock return variances. The arrival of information and the reaction of traders. *Journal of Financial Economics*, *17*(1), 5–26. https://doi.org/10.1016/0304-405X(86)90004-8

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics*, *91*(1), 24–37. https://doi.org/10.1016/j.jfineco.2008.02.003

Gharbi, S., Sahut, J. M., & Teulon, F. (2014). R&D investments and high-tech firms' stock return volatility. *Technological Forecasting and Social Change*, *88*, 306–312. https://doi.org/10.1016/j.techfore.2013.10.006

Gil-Garcia, R., & Puron-Cid, G. (2014). Using Panel Data Techniques for Social Science Research: an Illustrative Case and Some Guidelines. *CIENCIA Ergo-Sum, Revista Científica Multidisciplinaria de Prospectiva*, *21*(3), 203–216. http://www.redalyc.org/articulo.oa?id=10432355004

Gow, I. D., Kaplan, S. N., Larcker, D. F., & Zakolyukina, A. A. (2016). CEO Personality and Firm Policies. *NBER Working Papers*. https://ideas-repec-org.ezproxy2.utwente.nl/p/nbr/nberwo/22435.html

Goyal, A., & Santa-Clara, P. (2003). Idiosyncratic Risk Matters! *The Journal of Finance*, *58*(3), 975–1007. https://doi.org/10.1111/1540-6261.00555

Greve, H. R. (2003). A behavioral theory of R&D expenditures and innovations: Evidence from shipbuilding. *Academy of Management Journal*, *46*(6), 685–702. https://doi.org/10.2307/30040661

Gu, F., & Wang, W. (2005). Intangible Assets, Information Complexity, and Analysts' Earnings Forecasts. *Journal of Business Finance & Accounting*, *32*(9–10), 1673–1702. https://doi.org/10.1111/j.0306-686X.2005.00644.x

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

Hamim, & Tanvir, Md. (2020). R&D Investments and Idiosyncratic Volatility. *MPRA Paper*. https://ideas.repec.org/p/pra/mprapa/101330.html

Hoechle, D. (2007). Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence. *Https://Doi-Org.Ezproxy2.Utwente.Nl/10.1177/1536867X0700700301*, *7*(3), 281–312. https://doi.org/10.1177/1536867X0700700301

Holmstrom, B. (1989). Agency costs and innovation. *Journal of Economic Behavior and Organization*, *12*(3), 305–327. https://doi.org/10.1016/0167-2681(89)90025-5

Hun, M. P. (2011). Practical Guides To Panel Data Modeling : A Step by Step. *Public Management and Public Analysis Program*, 1–53. https://www.academia.edu/28505133/Practical_Guides_To_Panel_Data_Modeling_A_Step_by_Step

Kim, Y. S., & Park, K. J. (2020). R&D Spending and Stock Returns: Evidence from South Korea. *Asian Economic and Financial Review* , *10*(7), 744–757. https://doi.org/10.18488/JOURNAL.AEFR.2020.107.744.757

Lerner, J., Shane, H., & Tsai, A. (2003). Do equity financing cycles matter? Evidence from biotechnology alliances. *Journal of Financial Economics*, *67*(3), 411–446. https://doi.org/10.1016/S0304-405X(02)00256-8

Lev, B., & Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics*, *21*(1), 107–138. https://doi.org/10.1016/0165-4101(95)00410-6

Levi, S., & Zhang, X.-J. (2011). Do Temporary Increases in Information Asymmetry Affect the Cost of Equity? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1130667

Liu, H., Manzoor, A., Wang, C., Zhang, L., & Manzoor, Z. (2020). The COVID-19 Outbreak and Affected Countries Stock Markets Response. *International Journal of Environmental Research and Public Health 2020, Vol. 17, Page 2800*, *17*(8), 2800. https://doi.org/10.3390/IJERPH17082800

Malmendier, U., & Tate, G. (2005). CEO Overconfidence and Corporate Investment. *The Journal of Finance*, *60*(6), 2661–2700. https://doi.org/10.1111/J.1540-6261.2005.00813.X

Mason, P. A., & Hambrick, D. C. (1984). *Upper Echelons: The Organization as a Reflection of its Top Managers*. https://papers.ssrn.com/abstract=1504456

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

McConomy, B., & Xu, B. (2004). Value Creation in the Biotechnology Industry. *Cma Management*, *78*(2), 28–31. https://www-researchgate-net.ezproxy2.utwente.nl/publication/283924029_Value_creation_in_the_biotechnology_industry

Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance*, *42*(3), 483–510. https://doi.org/10.1111/j.1540-6261.1987.tb04565.x

Pérez-Rodríguez, J. V., & Valcarcel, B. G. L. (2012). Do product innovation and news about the R&D process produce large price changes and overreaction? The case of pharmaceutical stock prices. *Applied Economics*, *44*(17), 2217–2229. https://doi.org/10.1080/00036846.2011.562172

Rachev, S., Mittnik, S., Fabozzi, F. J., Focardi, S. M., & Jasic, T. (2007). *Financial econometrics : from basics to advanced modeling techniques*. Wiley. https://www-wiley-com.ezproxy2.utwente.nl/en-us/Financial+Econometrics%3A+From+Basics+to+Advanced+Modeling+Techniques+-p-9780471784500

Schmidheiny, K. (2022). *Panel Data: Fixed and Random Effects*.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under conditions of Risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Tebourbi, I., Wei, I., Ting, K., Thi, H., Le, M., Qian, |, Kweh, L., Pahang, M., Gambang, M., City, M., & Correspondence, V. (2020). R&D investment and future firm performance: The role of managerial overconfidence and government ownership. *Managerial and Decision Economics*, *41*(7), 1269–1281. https://doi.org/10.1002/MDE.3173

Ugur, M., Trushin, E., & Solomon, E. (2016). Inverted-U relationship between R&D intensity and survival: Evidence on scale and complementarity effects in UK data. *Research Policy*, *45*(7), 1474–1492. https://doi.org/10.1016/j.respol.2016.04.007

Xu, B. (2006). R&D strategy and stock price volatility in the biotechnology industry. *Review of Accounting and Finance*, *5*(1), 59–71. https://doi.org/10.1108/14757700610646943

Xu, B. (2011). Information Uncertainty, Capricious Behavior, and Share Price Volatility: Evidence from the Biotech Industry. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.908943

Zhang, W. (2015). R&D investment and distress risk. *Journal of Empirical Finance*, *32*, 94–114. https://doi.org/10.1016/J.JEMPFIN.2015.03.009

Zulfiqar, M., Zhang, R., Khan, N., & Chen, S. (2021). Behavior Towards R&D Investment of Family Firms CEOs: The Role of Psychological Attribute. *Psychology Research and Behavior Management*, *14*, 595–620. https://doi.org/10.2147/PRBM.S306443