THE EFFECT OF R&D INVESTMENT INTENSITY ON STOCK RETURN VOLATILITY: EVIDENCE FROM TECH FIRMS IN THE NETHERLANDS

Master Thesis

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Abstract

The empirical evidence suggests that R&D intensive firms have a higher stock return. However, there is only little research on the topic between R&D intensity and stock risk. This study addresses this gap using a sample of 44 Dutch tech firms from 2011 to 2019, where volatility is the measure of stock risk. The results show a strong positive relationship between R&D investment intensity and stock return volatility. However, the relationship becomes negative if we measure R&D investment intensity on a firm-specific level, because each firm has multiple observations over the years (panel data). This implies that if a firm decides to increase its R&D investment intensity, the risk for stock investors decreases. Although this might be explained by reaching a next stage in the R&D project, which requires additional investments. As the next stage is achieved, the uncertainty of the R&D investment decreases.

Author keywords: R&D investment intensity, total stock return volatility, idiosyncratic stock return volatility, Dutch firms, technology

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1. Introduction

Investments in research & development (R&D) are critical for a firm to survive. Firms have to keep improving their products and their processes to distinguish themselves from their competitors in the market. Furthermore, innovation is important in order to discover and ultimately satisfy customer demand, which changes over time (Karlsson et al., 2004). The customer is willing to pay a higher price if it satisfies his or her needs and expectations, which is beneficial for the firm. So, the successfulness of a R&D project influences the (future) performance of the firm (Hoskisson & Hitt, 1988). However, there is no guarantee that the costs that are spent on R&D will be recouped in the future. Although investments in R&D projects could increase firm performance, the associated risks increase as well due to the chance of failing R&D projects.

On the other side, there are stock investors who want to benefit from successful R&D projects, but they want to avoid firms with failing R&D projects. This leads to uncertainty for stock investors as well. Moreover, investors have less information than insiders. This means that employees of the company are more capable of estimating if the R&D investments will be profitable in the longer term. This phenomenon is also known as information asymmetry (Giambona et al., 2018). If there is more discrepancy in the availability of information, the increasing uncertainty could result in more risk for the stock investor.

Stock return volatility is a widely used measure of risk (Gharbi et al., 2014). Stock return volatility is a statistical measure of stock risk, measured by the standard deviation of stock returns. If a stock fluctuates more in value than another stock, i.e., a higher standard deviation of stock returns, then it has a higher volatility. Another measure of stock risk that is often used, is the beta (Tsai et al., 2019). It is a measure of the volatility of a stock in relation to the overall market, where the overall market has a beta of 1. If a single stock is riskier than the market, it has a beta higher than 1. If a stock has a low beta, it reflects that the stock is less risky.

There are already several researchers that have investigated the effect of R&D investment on stock return. For example, Chen et al. (2020) studied this relationship for U.S. firms, Lu (2020) for Chinese firms, and Kim and Park (2020) for firms in South Korea. Duqi et al. (2011) studied the relationship between R&D investment and stock return among fourteen of the most industrialized in Europe, including the Netherlands. The study from Duqi et al. (2011) is the only study that included the Netherlands to test the relationship between R&D investment and stock return. Although stock risk and stock return look like two related concepts, they are two different topic areas.

Moreover, there are only a few researchers that studied the effect of R&D investment on stock return volatility. Almost all of them are considered U.S. firms (Fung, 2006; Jiang et al., 2020; Mazzucato & Tancioni, 2012; Xu, 2006a; Xu, 2006b). Only Gharbi et al. (2014) did not focus on U.S. firms. Instead, they focused on firms in France. All existing studies have in common that they only included tech firms in a specific industry, except Jiang et al. (2020). The latter included all public firms in the S&P 500. The reason why the other researchers included only tech firms, is that these firms spend on average more on R&D than other types of firms. This study proves if the relationship holds for another European country, the Netherlands. Therefore, this study contributes to the little existing literature on this topic.

This study distinguishes itself from the existing literature in several ways. First, in this study the full sample consists of Dutch firms, whereas Dutch firms only covered four percent (72 firms) in the study from Duqi et al. (2011). Other similar studies did not include the Netherlands at all. Second, in this study only tech firms are included, whereas other studies included only high-tech firms (Gharbi et al., 2014) or all types of firms (Jiang et al., 2020). Tech firms are more R&D intensive than other types of firms. Third, the relationship between R&D investment and stock return volatility is investigated. This topic received little attention from researchers so far, whereas there are a lot of studies on the topic of R&D and stock return. Fourth, the time span in this study covers the most recent period (2011 to 2019). This makes the findings up to date.

This study provides an answer to the following research question: "What is the effect of R&D investment on stock return volatility for tech firms in the Netherlands?" So, the aim of this study is to identify the effect of R&D investment intensity on stock price volatility to provide an answer to stockholders if R&D intensive tech firms are riskier investments. To answer this research question, two hypotheses are developed. These hypotheses are based on several theories and empirical evidence in existing literature.

This study builds on the existing literature in several ways. First, stock return volatility is divided into two concepts: total stock return volatility and idiosyncratic (firm specific) stock return volatility. Second, only tech firms are analysed. These firms spend on average more money on R&D and depend more on successful R&D investments to survive. Third, the sample period should cover the most recent years to avoid conclusions that could be outdated. Therefore, this study covers the period from 2011 to 2019. Regression analysis (OLS and FE) is used to investigate the link between R&D investment intensity and stock return volatility while controlling for firm characteristics.

The results suggest that stock return volatility increases significantly if the R&D investment intensity becomes higher. This could not be explained by systematic volatility, as the results hold for total stock return volatility and idiosyncratic stock return volatility. However, these general findings do not hold when we consider that several observations are related to one firm (i.e., a panel dataset). The FE results show that if a firm decides to increase its R&D investment intensity compared to other years, the stock return volatility decreases significantly. These findings do hold in the OLS regression robustness test, where R&D investment intensity is transformed to a firm-specific intensity variable.

This study makes a number of practical contributions. Stock investors should be aware that R&D intensive Dutch tech firms have a riskier stock than the firms who do invest in R&D. However, it is a good sign if a firm decides to increase its R&D investment intensity. On the firm-specific level, stock return volatility decreases if R&D intensity increases. This is a practical contribution to the management as well. It implies that increasing the R&D intensity creates trust for stock investors and reduces the stock return volatility. So, increasing the R&D intensity has a positive signal towards stock investors.

The remainder of this study is constructed as follows. Section 2 considers the literature on R&D investment intensity and stock return volatility. Several theories are mentioned to support the hypotheses of this study. Section 3 describes the methodology, including the explanation of the variables, the research method, and the research model. Section 4 presents more information on the data and the descriptive statistics. Section 5 provides the empirical results of this study. Section 6 discusses theoretical and practical contributions of the findings, and the limitations of this study.

2. Literature Review

In this chapter, the relevant literature to this study is analysed. The first part of this literature review provides more theoretical background about R&D investment intensity and stock return volatility. The second part focuses on empirical evidence of both concepts and the relationship between R&D investment intensity and stock return volatility. The final part of the literature review combines the theories and the empirical evidence into hypotheses that are tested in this study.

2.1 R&D investment intensity: Theoretical background

R&D investment intensity is the intensity of how much a firm spends on research and development. For example, the intensity of R&D expenses to total sales (Gharbi et al., 2014; Jiang et al., 2020; Mazzucato & Tancioni, 2012). The main difference from investments in plant, property and equipment is that these are tangible assets, whereas investments in R&D are intangible. For tangible assets, it is easier to calculate how much value they add. It reduces the risk of the investment. However, intangible assets are complex and hard to copy, which could create a competitive advantage (Hitt et al., 2001). However, it is uncertain if and how much value they will add for the company.

There are several theories that explain R&D investment intensity. First of all, there is the behavioural theory. The behavioural theory assumes that R&D investment intensity increases when firm performance is low or when there is excess capital (Greeve, 2003; Rhee et al., 2019). Low firm performance gives managers an incentive to take more risks. On the other hand, when firm performance is high, the incentive to take more risk disappears. Therefore, the inertia theory assumes that high firm performance suppresses R&D investment intensity more than low firm performance increases them (Greve, 2003). The reason for this is that past knowledge and past experience replaces the need for new knowledge (Jiang et al., 2018).

Another theory in relation to R&D is the social exchange theory. This theory assumes that R&D expenditure is spent more effectively if the employees have more social skills, such as a good network and interpersonal skills (Garud & Prabhu, 2021). Contradicting this theory is the Schumpeterian theory. The prediction of this theory is that a sustainable growth in productivity can only be achieved if a sustained fraction of GDP is spent on R&D (Ha & Howitt, 2007). This implies that a firm cannot use their R&D expenditure more effectively internally (social exchange theory) or externally (absorptive capacity theory). The absorptive capacity assumes that a firm is able to learn from the environment, which creates new opportunities for the firm (Griffith et al., 2003; Qian & Acs, 2013).

Firms invest in research and development (R&D) for several reasons. The first reason is to keep improving their products and their processes to distinguish themselves from the competitors in the market. Furthermore, innovation is important in order to discover and ultimately satisfy customer demand, which changes over time (Karlsson et al., 2014). The customer is willing to pay a higher price if it satisfies his or her needs and expectations, which is beneficial for the firm. This is stimulated by governments through the issuance of patents. Patents result in a temporary monopoly for the firm, because competitors are not allowed to copy-paste this innovative idea during that period. The patent allows investors a greater share of the returns from their innovations (Czarnitzki & Toole, 2011). This increase in performance is an extra benefit of investing in R&D.

However, there is no guarantee that the costs that are spent on R&D will be recouped by the firm. A firm may not even get to the step of applying for a patent. For example, because there is a lack of human capital, a lack of financial resources or a lack of technical capabilities of the firm (Link & Wright, 2015). Even if the three factors are in balance, success is still not certain. Baker et al. (1986) argues that this uncertainty of success or failure is due to technical and/or commercial reasons. Technical reasons include internal mistakes, like unclear goals from the start of the R&D project, and commercial reasons cover external influences, such as market uncertainty. There are also disadvantages related to competitors. They could spend on R&D as well and come up with a solution that is better or earlier in the market. Another example is that sensitive information leaks to competitors.

However, this is not a reason that deters firms from investing in R&D. Statistics Netherlands, also known as CBS, is a Dutch governmental institution that gathers statistical information from the Netherlands. This institution published key figures about R&D as well (CBS, 2020). This data is plotted in figure 1. The left plot shows the expenditure on R&D activities in the Netherlands between 2013 and 2019, whereas the right plot shows the number of firms that contributed to this R&D expenditure. Figure 1 shows that the percentage from GDP that is spent on R&D is quite steady each year. GDP increased each year, but this was also the case for the R&D expenditures in total. However, this does not apply for the number of firms that contributed to R&D expenditure. Mainly from 2016 onwards, the increasing trend does not continue. It implies that the number of firms does not affect the R&D expenditure as a percentage of the GDP in the Netherlands.

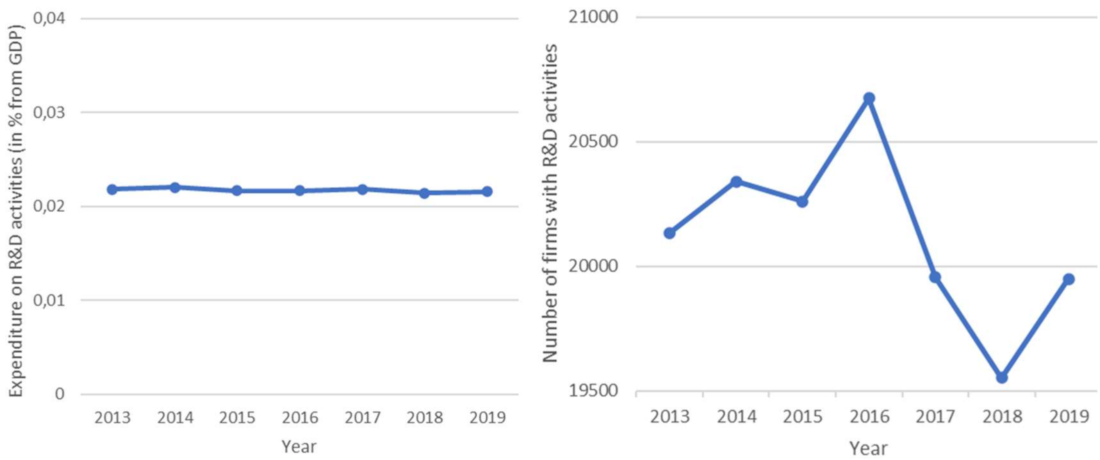

Figure 1: Expenditure on R&D activities (in % from GDP) and the number of firms with R&D activities in the Netherlands between 2013 and 2019 (CBS, 2020).

2.2 Stock return volatility: Theoretical background

Listed firms sell their stock on the stock exchange. The value of the stock reflects the underlying value of the firm and can change at any time. Stock return is the amount of money that is made or lost on the investment over a period of time. Stock return volatility is a statistical measure of stock risk, measured by the standard deviation of stock returns. If a stock fluctuates more in value than another stock, i.e., a higher standard deviation of stock returns, then it has a higher volatility. Stock return volatility is a widely used measure of risk (Gharbi et al., 2014). Another measure of stock risk that is often used, is the beta (Tsai et al., 2019). It is a measure of the volatility of a stock in relation to the overall market, where the overall market has a beta of 1. If a single stock is riskier than the market, it has a beta higher than 1. If a stock has a low beta, it reflects that the stock is less risky.

There are different types of volatility. First of all, there is total stock volatility. This is the total realized variation in stock prices (Jiang et al., 2020). It measures the entire financial risk surrounding the firm's stock (Gharbi et al., 2014). Total stock volatility can be divided into two parts: a firm specific part and a market related part. Idiosyncratic (or firm specific) stock volatility estimates the impact of specific firm investment on firm specific volatility (Gharbi et al., 2014). It is the variance of the residual from an asset-pricing model (Aabo et al., 2017). The most famous asset-pricing model is the capital asset pricing model, also known as CAPM model. According to Aabo et al. (2017), idiosyncratic volatility represents about 85% of the total stock volatility. Systematic (or market related) stock volatility is the volatility that is inherent to the entire market and cannot be diversified. It does not affect a particular stock, but it affects the overall market (Abdoh & Liu, 2021).

In theory, there is no relationship between idiosyncratic stock volatility and expected stock return. Firm specific events can be eliminated by holding a diversified portfolio. Investors will not receive additional returns for bearing extra risks, according to the CAPM model (Malkiel & Xu, 1997). However, in practice there is a positive relationship between idiosyncratic stock volatility and expected return. This is confirmed in the study from Chen et al. (2017), who found that Chinese stock return volatility results in a higher stock return. An unexpected increase in idiosyncratic stock volatility represents deterioration in investment opportunities (Chen et al., 2017).

According to Li et al. (2021), economic uncertainty is the most important factor to explain idiosyncratic stock volatility. Risk-averse investors dislike uncertainty and contribute to an increase in idiosyncratic stock volatility. Another factor that influences idiosyncratic stock volatility is the amount of intangible assets. The reason is that companies produce and accumulate intangible capital as part of their normal operations, whereas this capital covers a future value (Li et al., 2020). Finally, Aslanidis et al. (2019) argue that macro-finance factors influence idiosyncratic stock volatility. These factors create market imperfections, which make perfect diversification impossible.

The relationship between systematic stock volatility and expected stock return is in theory positive. The higher the beta of a stock, the higher the expected returns (Hundal et al., 2019). This reasoning is based on the CAPM model. A higher volatility is reflected in a higher beta, and this results in a higher expected stock return. Beta reflects in this case the stock risk. Therefore, stock return volatility and expected stock return should be positively related. However, size measures seem to be proxies for the variety of systematic risk (Malkiel & Xu, 1997). As a result, there seems to be no relationship between systematic risk and stock return.

The CAPM model consists of three factors. The first factor is the beta, which covers the risk factor. It measures the sensitivity of an individual stock compared to the overall market (Yang & Hu, 2021). The other two factors are the riskless rate of interest and the risk premium on equity. These affect the current value of the market index and the future stock prices (Binder & Merges, 2001). Another factor that influences systematic stock volatility is macroeconomic variables (Aktas, 2011). Investors receive and evaluate new information about the macroeconomic variables and influences the behaviour of stock investors.

2.3 R&D investment intensity and stock return volatility: Theoretical background

2.3.1 Behavioural theory and risk theory

There are several theories that explain the relationship between R&D investment intensity and stock return volatility. First of all, the behavioural theory, which is discussed earlier, assumes that R&D investment intensity increases if a firm underperforms or has access to excess capital (Greve, 2003). The risk theory supports the former argument, where firms are more likely to be risk tolerant if the firm is in hard financial times. The top management team are willing to take more risks, such as investing in R&D, if they cannot meet shareholders' interests in the long term (Hu et al., 2019). However, a clear long-term objective of the R&D project is missing in most of these cases, which increases the likelihood of failing R&D projects (Baker et al., 1986). This uncertainty is reflected in an increasing stock return volatility, as the future of the firm depends more on the success of the R&D projects. The level of uncertainty depends on four factors: the level of information asymmetry, the type of financing for a R&D project, the stage of the R&D project and the announcements of the R&D developments.

First of all, there is a level of information asymmetry. Investors have less information than insiders. This means that employees of the company are more capable of estimating if the R&D investments will be profitable in the longer term. This phenomenon is also known as information asymmetry (Giambona et al., 2018). If there is more discrepancy in the availability of information, the increasing uncertainty could result in more risk for the stock investor. Gharbi et al. (2014) argue that there is a positive relationship between R&D investment intensity and stock return volatility. They mention that R&D investments result in more information asymmetry between insiders and investors. Insiders could better estimate the success probability, the prospects, and the future profit. This is not the case for investors, and therefore they require a higher expected stock return.

At the same time, Jiang et al. (2020) argue that the degree of information asymmetry is related to the type of financing. If firms depend on external equity financing to continue with their R&D project, then they are forced to provide more information about their R&D-project compared to firms who can rely on external debt. On the other hand, if a firm provides too much information about their R&D projects, then competitors may benefit from this information. A solution for this problem is applying for patents, which ensures that only the firm can benefit from the new innovation. Mazzucato and Tancioni (2012) expect that there is a relationship between innovation and stock return volatility, where innovation is measured as R&D spending and patents. Their reason is that R&D investments include more uncertainty compared to investments in tangible assets and this uncertainty is reflected in the volatility. However, Mazzucato and Tancioni (2012) do not mention the direction of the relationship.

Last of all, there is Xu (2006a) who assumed that there is a relationship between R&D investment intensity and stock return volatility, but that this relation is affected by three factors. First of all, the R&D progress. This means that there is a different level of uncertainty in each stage of the R&D project: the further the stage, the lower the uncertainty. The second factor is the success rate. Xu (2006a) argues that the stock price volatility decreases if the success rate increases. His third hypothesis supposes that the post announcement drift decreases in R&D progress, because there is less R&D uncertainty. To conclude, there might be a relationship between R&D investment intensity and stock return volatility, but this could be affected by the stage and announcements of the R&D developments.

2.3.2 Absorptive capacity theory and inertia theory

A contradicting theory is the absorptive capacity theory. Absorptive capacity is the ability to learn from the environment and make financial benefits out of it. The theory suggests that R&D-based absorptive capacity should have a positive influence on productivity growth (Griffith et al., 2003). Therefore, the risk of the R&D projects is reduced. This implies that the stock return volatility is lower for mature R&D departments, who are more capable of transforming the opportunities from the environment into benefits for the firm (Schiele, 2007). Instead of learning from the environment, it is also possible to go through a learning curve. This is known as knowledge spillovers. Knowledge spillovers enable firms to learn from their own mistakes as well as mistakes made by competitors. Fung (2006) expected a positive relation between R&D and stock volatility, but knowledge spillovers should reduce the stock volatility. On the other hand, when firm performance is high, the incentive to take more risk disappears. Therefore, the inertia theory assumes that high firm performance suppresses R&D investment intensity more than low firm performance increases them (Greve, 2003). The reason for this is that past knowledge and past experience replaces the need for new knowledge (Jiang et al., 2018).

2.4 R&D investment intensity: Empirical evidence

There are contrary results whether R&D investments increase or decrease the market performance of firms. Hoskisson and Hitt (1988) found a positive relation between R&D intensity and market performance for non-diversified firms. On the other hand, they found a negative relationship for the same relation for diversified firms. The difference in valuation by the market is caused by the underlying reason to invest in R&D. Whereas diversified firms are more likely to spend on R&D for their hedging strategy and non-diversified firms for synergistic innovation. Similar results were found in the study from Andrade et al. (2018). They found that if firms are closer to the technological frontier, they have a higher return on their R&D investments. These firms are more likely to be specialized, non-diversified firms.

Further, Chen and Hsu (2009) found a negative relationship between family ownership and R&D investment intensity for Taiwanese firms. It indicates that firms with higher levels of family ownership spend less on R&D, either because they spend their money on R&D more efficiently or because they are more likely to avoid these risky investments. On the other hand, there is a positive relationship between women on the board and R&D spending (Saggese et al., 2020). The sample consisted of Italian firms in the high-tech industry. Moreover, they found that the more mature and powerful the women are, the stronger the relationship is. It implies that women stimulate the input of innovation. However, monitoring as a corporate governance mechanism seems to have no effect on R&D investment intensity. Kor (2006) found that monitoring by outside executives does not have a significant impact on the R&D investment strategy of the firm.

Subsidies contribute to the R&D investment intensity. Almus and Czarnitzki (2003) executed a study in Eastern Germany and found that firms that received public R&D subsidies spend more on R&D than firms that were not backed by those public subsidies. The impact of the subsidy was that innovation activities increased by about four percentage points. Furthermore, Nadiri and Mamuneas (1994) tested the impact of R&D capital on cost structure and performance. The consequence of increasing R&D capital is productivity growth, but the impact on the cost function is negative except in six industries. These industries are focused on services and benefit less from R&D investments related to the cost structure.

2.5 Stock return volatility: Empirical evidence

According to Lee and Liu (2011), there is a U-shaped relationship between the stock price informativeness and idiosyncratic stock return volatility. When the information environment of the firm is relatively poor or relatively good, then this leads to more firm-specific return volatility. Moreover, the level of information quality has a negative impact on the stock return volatility (Chen et al., 2012). Which means that lower information quality results in more stock return volatility. The amount and the quality (managerial discretion) of the information both contribute to information symmetry. If there is less transparency and more uncertainty, it results in more risk for the investor. This increasing risk is reflected in a higher stock return volatility. Kiymaz and Berument (2003) collected international evidence that the day of the week had an effect on stock market volatility. However, further analysis found that this relationship is caused by another variable: trading volume. On days where trading volume is low, stock return volatility is higher.

Besides those firm-specific factors, there are also macroeconomic factors that influence stock return volatility. For example, terrorism has a significant effect on stock return volatility (Arin et al., 2008). This effect is larger in emerging markets, where the trust in, and quality of, institutions is lower. A contrasting finding is found in the study from Degiannakis et al. (2014), who found that oil price chances reduce the volatility in European stock markets. This is remarkable, because oil price chances are a systematic risk for investors, which cannot be avoided by diversification. Therefore, it is likely to expect an increase in stock market volatility due to chances in oil prices. However, the findings imply that chances in oil prices are perceived as good news for energy companies.

2.6 R&D investment intensity and stock return volatility: Empirical evidence

There are only a few researchers that studied the effect of R&D investment on stock return volatility. Almost all of them are considered U.S. firms (Fung, 2006; Jiang et al., 2020; Mazzucato & Tancioni, 2012; Xu, 2006a; Xu, 2006b). Only Gharbi et al. (2014) focused on firms in France. All existing studies have in common that they only included tech firms in a specific industry, except Jiang et al. (2020). The latter included all public firms in the S&P 500. The reason why the other researchers included only tech firms, is that these firms spend on average more on R&D than other types of firms.

Gharbi et al. (2014) found a strong and positive relationship between R&D investment intensity and stock return volatility for French high-tech firms during the period 2002-2011. This study tested two hypotheses, where stock return volatility was measured as total stock return volatility and in the other hypothesis as idiosyncratic (firm specific) stock volatility. Both hypotheses were confirmed. Another research that tested the same relationship is the research from Jiang et al. (2020). They divided idiosyncratic stock return volatility into two different components. The sample consisted of U.S. firms in the S&P 500 index covering the period 2003-2017. The researchers found a positive relationship between R&D investment intensity and one measure of idiosyncratic stock return volatility. However, they found a negative relationship between R&D investment intensity and the other measure of idiosyncratic stock return volatility. Nevertheless, the effect on the total stock return volatility remains positive and significant.

Mazzucato and Tancioni (2012) added another variable to the bivariate relationship: patents. Patents and R&D investments cover both the innovativeness of a firm. The third concept, stock return volatility, is measured as idiosyncratic (firm specific) volatility. The study analysed U.S. pharmaceutical firms between 1974 and 1999. The researchers found a positive relationship between stock return volatility, R&D intensity, and the number of patents. They conclude that innovation is related to more uncertainty. Instead of adding patents to the bivariate relationship, Fung (2006) added knowledge spillovers. This concept means learning from others. Only U.S. firms in the chemical, computer, and electrical and electronic industry were included in the sample. The sample period ranged from 1983 to 1997. Again, this study supported the positive relationship between R&D investment intensity and stock return volatility. However, knowledge spillovers reduce the amount of stock return volatility.

2.7 Hypotheses development

This study gives rise to two hypotheses. These hypotheses are based on theoretical models and empirical evidence from existing literature that is discussed in previous sections. The first hypothesis is in line with the studies from Fung (2006), Gharbi et al. (2014) and Jiang et al. (2020). This hypothesis is about the relationship between R&D investment intensity and total stock return volatility. All studies reported a positive relationship between the two concepts. The theoretical reasoning is that R&D investments increase the uncertainty for stock investors. It is expected that the increasing risk is reflected in an increasing total stock return volatility. Therefore, the first hypothesis states: H1: *A firm with higher R&D investment intensity tends to have a higher total stock return volatility.*

Instead of using total stock return volatility, several researchers used idiosyncratic stock return volatility as another measure to test the relationship between R&D investment intensity and stock return volatility (e.g., Mazzucato & Tancioni, 2012; Gharbi et al., 2014). R&D investments are specific to the firm and the success depends on the human capital and resources within the firm. Furthermore, some firms might have more difficulties with creating R&D output. Idiosyncratic stock volatility allows us to estimate the impact of specific firm investment on firm specific volatility (Gharbi et al., 2014). Therefore, the second hypothesis states: H2: *A firm with higher R&D investment intensity tends to have a higher idiosyncratic stock return volatility*.

3. Methodology

In this chapter, the methodology of this study is described. The first part provides more information about the variables that are considered in this study. The second part focuses on the research method. In this case, regression analysis is used to analyse the data. The final part of this chapter combines the several variables and the research method into a research model. As there are two dependent variables, there are two models as well.

3.1 Variables

The first part of this methodology chapter provides more information about the several variables. This study tests the relationship between R&D investment intensity and stock return volatility. R&D investment intensity is considered as the independent variable and stock return volatility as the dependent variable. Moreover, there are several control variables included to avoid biased conclusions.

3.1.1 Independent variable: R&D investment intensity

The independent variable in this model is R&D investment intensity. This variable is measured in the same way as in several comparable studies (Gharbi et al., 2014; Jiang et al., 2020; Mazzucato & Tancioni, 2012). Specifically, the research & development investment intensity (RDII) is measured as the ratio of R&D expenses to total sales. This means that the variable is considered as a continuous variable. Another measure for R&D is patents. The difference is that investment intensity is an input variable and patents an output variable (Mazzucato & Tancioni, 2012). The uncertainty that is caused by R&D is related to the input and not to the output. Therefore, R&D investment intensity is more appropriate than the number of patents.

3.1.2 Dependent variable: stock return volatility

The dependent variable in this model is stock return volatility. It is expected that this variable depends on the independent variable, namely R&D investment intensity. First of all, the interval scale of the stock return should be determined. This could be measured on multiple interval scales. For example, at a one-minute interval (Jiang et al., 2020), daily interval (Xu, 2006a; Xu, 2006b), weekly interval (Gharbi et al., 2014) or a monthly interval (Mazzucato & Tancioni, 2012). However, it might become too complex to collect the one-minute interval stock values, due to data availability. Moreover, daily intervals may be biased by the day of the week, as is discussed in the literature review. This is because of the difference in trading volumes on a day. Investors are aware of this. Therefore, it is decided that the weekly intervals are the most appropriate interval scale to calculate stock return.

The second step is to determine the stock return volatility. This is calculated as the standard deviation of the stock returns over a specific period. In this case, annualized standard deviations is the most appropriate measure. This is because RDII is also calculated on an annual basis. Furthermore, this is in line with the study from Gharbi et al. (2014), Mazzucato and Tancioni (2012), Xu (2006a) and Xu (2006b). As mentioned in the literature review, stock return volatility is distinguished into total stock return volatility (TSRV) and idiosyncratic stock return volatility (ISRV). TSRV is measured as the annualized standard deviations of weekly returns. ISRV is measured as the annualized standard deviations of weekly errors from the CAPM model. This is also in line with the study from Gharbi et al. (2014). The ISRV takes greater account of firm-specific volatility than the TSRV.

3.1.3 Control variables

To avoid biased conclusions, several control variables are included to test the relationship between R&D investment intensity and stock return volatility. The first studies who tested this relationship did not include many control variables. For example, Mazzucato and Tancioni (2012) only included firm size as a control variable, whereas Gharbi et al. (2014) included size and leverage as control variables. More recently, the study from Jiang et al. (2020) contained seven control variables. Five out of these seven control variables were significant at the 1% level and are therefore included in this study as well. The five control variables in this study are: firm size, leverage, return on assets, growth opportunity and firm age. Moreover, dummy variables are included to distinguish between the different tech levels and years.

All variables are in line with the study from Jiang et al. (2020). First, firm size (SIZE) is measured as the natural logarithm of book value of total assets. Larger firms could invest more money (absolute) than smaller firms. Second, leverage (LVRG) is calculated as total long-term debt divided by total assets. If firms have more debt, they are more likely to provide more information to external parties to obtain this debt. Moreover, interest affects the future cash flows. Third, return on assets (ROA) is calculated as net income divided by total assets. Fourth, growth opportunity (GROW) is measured as the sum of the market value of equity and book value of long-term debt, divided by total assets. Fifth, firm age (AGE) is measured by the natural logarithm of the number of years since the firm was founded. The last control variables are dummies to distinguish between different tech levels (TECH) and between different years (YEAR). An overview of all variables and definitions can be found in table 1.

Variables	**Abbreviations**	**Definitions**
R&D investment intensity	RDII	Ratio of R&D expenses to total sales
Total stock return volatility	TSRV	Annualized standard deviations of weekly returns in year t
Idiosyncratic stock return volatility	ISRV	Annualized standard deviations of weekly errors from the CAPM model in year t
Firm size	SIZE	The natural logarithm of book value of total assets
Leverage	LVRG	Total long-term debt divided by total assets
Return on assets	ROA	Net income divided by total assets
Growth opportunity	GROW	The sum of the market value of equity and book value of long-term debt, divided by total assets
Firm age	AGE	Firm age measured by the natural logarithm of the number of years since the firm was founded
Tech dummy	TECH	Dummy variables to distinguish between high-tech, medium-high-tech, medium-low-tech, and low-tech
Year dummy	YEAR	Dummy variables to distinguish between years (2011-2019)

Table 1: Definitions of the variables

3.2 Research method

Regression analysis is the most common method that is used in similar studies. Nonetheless, there are some different types of regression analysis. For example, Fung (2006) used ordinary least squares (OLS) regression to test his hypotheses. The OLS estimator has the advantages that it is precise with little standard error. On the other hand, the OLS estimator could be biased. To test this problem, a Wu-Hausman test should be conducted to check the endogeneity issues. This is reflected in the error term, which shows an imperfect relationship between the dependent variable and one or more independent variables. The goal of OLS is to show the regression where the sum of squares in the difference between the observed and predicted values of the dependent variable is the smallest. Jiang et al. (2020) also used ordinary least squares regression, but they included two-stage least squares (2SLS) regression and Tobit regression as well. The 2SLS regression avoids potential biased results caused by endogeneity issues in the OLS regression.

On the other hand, Gharbi et al. (2014) and Mazzucato and Tancioni (2012) used three other specifications from regression analysis. Namely, a model for pooled regression, a model for fixed effects and a model for random effects. The pooled regression assumes a fixed constant for all firms, whereas the model for fixed effects allows the constant to differ between firms. This allows firm level factors to influence the relationship. This model assumes that firm-specific effects are correlated with the independent variables. Finally, the model for random effects has a constant which is a random variable. This means that the constant is an error component. Firm-specific effects are assumed to be uncorrelated with the independent variables. So, the difference in outcomes for the three methods is the value of the constant in the formula. Gharbi et al. (2014) mentioned that the fixed effects model was the most appropriate test for their study, because of the significance level of several statistical tests.

Therefore, regression analysis is used in this study to analyse the data. The specific type of regression analysis depends on the data and which type is the most appropriate in that situation. The purpose of regression analysis is to estimate a model to analyse the relationship between (an) independent variable(s) and a dependent variable. All independent variables have to be metric. If a dependent variable is nominal, then dummy variables could be included with one reference category (the tech dummy). The disadvantage of regression analysis is that it only measures linear dependency between variables. So, this assumption has to be fulfilled to use regression analysis as a research method. If this assumption is fulfilled for this study will be checked in section 5.2. All statistical analyses are conducted via SPSS.

3.3 Research model

The purpose of the research model is to examine if there is a relationship between R&D investment intensity and stock return volatility. The fact that there are two measures for the dependent variable stock return volatility results in two different models. As mentioned, the research method behind the models is regression analysis. The models in this study are based on nine variables: one independent variable, two dependent variables and seven control variables. Model 1 tests the relationship between R&D investment intensity and total stock return volatility and model 2 tests the relationship between R&D investment intensity and idiosyncratic stock return volatility. Therefore, the models can be presented as follows:

Model (1): $(TSRV)_{it} = \beta_0 + \beta_1(RDII)_{it} + \beta_2(SIZE)_{it} + \beta_3(LVRG)_{it} + \beta_4(ROA)_{it} + \beta_5(GROW)_{it} + \beta_6(AGE)_{it} + \beta_7(TECH\ Dummy)_{it} + \beta_8(YEAR\ Dummy)_{it} + \varepsilon_{it}$

Model (2): $(ISRV)_{it} = \beta_0 + \beta_1(RDII)_{it} + \beta_2(SIZE)_{it} + \beta_3(LVRG)_{it} + \beta_4(ROA)_{it} + \beta_5(GROW)_{it} + \beta_6(AGE)_{it} + \beta_7(TECH\ Dummy)_{it} + \beta_8(YEAR\ Dummy)_{it} + \varepsilon_{it}$

Where i represents the individual company and t each observed year in this study. Further, the error term reflects the unobserved random error in the dependent variables.

4. Data

In this chapter, more information is provided about the relevant data in this study. The first part focuses on the data collection. This covers topics as how the data is selected and where the data comes from. The second part gives a summary of the data, also known as the descriptive statistics.

4.1 Data collection

The main concepts in this study are R&D investment intensity and stock return volatility. R&D investment intensity and the other firm characteristic control variables are available in the Orbis database. These firm characteristic control variables consist of firm size, leverage, return on assets, growth opportunities, firm age, and tech and year dummies. These control variables are included to avoid biased conclusions. The stock price history, to calculate the stock volatility, from all firms is available in open databases. For example, the Orbis database is a useful database. The stock exchange is transparent for insiders, stock investors and outsiders.

As mentioned in the research question and in the research goal, this study focuses on tech firms in the Netherlands. Although the Netherlands is a small country, it is placed fifth in the top 25 of smartest countries in the world according to Forbes (2019). First of all, only Dutch listed firms are considered. From this sample, only the tech firms are considered. Eurostat (2008) divided the manufacturing industry into four categories, based on technological intensity. All firms in high, medium-high, medium-low, and low-technology industries are included in the sample. Each Dutch firm is classified in a specific industry and this industry is reflected in a 2-digit NACE Rev. 2 code. With the help of this code, it is possible to divide each company into a specific group. This code is available in the Orbis database. In total, there are 52 Dutch firms that can be divided in one of the four groups. Dead firms are included in the list as well to avoid survivorship bias.

However, there are three firms that are included in the list twice: Hunter Douglas, Philips and Value8. These firms are listed twice, because one is the common stock, and one is the preferred stock. The preferred stock is removed from the list, because other firms in the list also only have the common stock. Furthermore, there are five firms that only provide data that is not relevant for this study. For example, because they were not listed anymore in 2011 or became listed after 2019. This makes a total sample of 44 firms. From 28 firms the full data is available from 2011 to 2019. The other 16 firms have only information for some years, because they were listed after 2011 or delisted before 2019. There are in total 317 observations. A list of the firms that are part of the sample with their NACE Rev. 2 classification can be found in Appendix 1.

The last sampling criterion that has to be discussed is the sample period. The sample period in this study ranges from 2011 to 2019. The Orbis database only provides data from the last ten years. For most firms, this is from 2011 to 2020. However, not all firms have their annual report from 2020 published yet. Therefore, only data from 2010 to 2019 is available. As a result, the sample period from 2011 to 2019 is the most appropriate. It is important to investigate the most recent developments to have a study that does not base their results on possible outdated information.

4.2 Descriptive statistics

Table 2 shows the descriptive statistics of the variables that are used in this study. Outliers are winsorized at the 1st and 99th percentile for all variables to avoid biased results. The mean (median) for total stock volatility (TSRV) is 32.4% (26.7%) and for idiosyncratic stock volatility (ISRV) 28.9% (23.2%), respectively. It confirms that idiosyncratic volatility represents about 85% of the total stock volatility, which is in line with the findings from Aabo et al. (2017). This is the case for the mean as well the median. The last main variable in this study is R&D investment intensity (RDII). The Dutch tech firms invest on average 4.8% of their sales on R&D, whereas the median of R&D intensity is 0.3%. This implies that most Dutch tech firms do not invest in R&D. Indeed, 147 of the 317 observations (46.4%) report no R&D expenses.

The other variables are the control variables that are used in this study (table 2). The mean and median for firm size (SIZE) is 5.94. Similar results for the mean and median can be found for the leverage (LVRG), 0.15 and 0.14 respectively. This implies that the average firm's long-term debt is about 15% of the total assets. The total range of long-term debt to total assets is from 0% to 58%. The mean (median) return on assets (ROA) is 1.5% (4.3%). However, there are also firms that have a negative return on assets, which means that there is a loss. The mean and median for the growth opportunities (GROW) is 1.26 and 1.01. A value of 1 implies that the book value of the equity equals the market value of the equity. This is almost the case for the median firm. Finally, there is the firm age (AGE). This variable is transformed to a logarithm with a mean of 3.75 and a median of 3.74.

Furthermore, this study contains dummy variables for year and industry. Table 3 shows an overview of the descriptive statistics of the variables across the four industries. With regard to the mean and the median of the stock return volatility measures, it appears that it increases if the industry is more technical. The only exception is the medium-high-tech industry, who has lower values compared to the other industries.

Variable	Mean	Median	Std. dev.	Min.	Max.
TSRV	0.3235	0.2668	0.18063	0.13	1.18
ISRV	0.2889	0.2320	0.18277	0.11	1.18
RDII	0.0479	0.0034	0.15768	0.00	1.26
SIZE	5.9415	5.9385	1.11785	3.30	7.91
LVRG	0.1514	0.1422	0.12144	0.00	0.58
ROA	0.0148	0.0425	0.14487	-0.65	0.39
GROW	1.2622	1.0071	0.89433	0.30	4.63
AGE	3.7529	3.7377	1.24303	0.11	6.06

Table 2: Descriptive statistics of the variables

	TSRV mean	TSRV med.	TSRV s.d.	ISRV mean	ISRV med.	ISRV s.d.
Low	0.3211	0.2295	0.23573	0.3017	0.2148	0.24126
Med-low	0.3263	0.2993	0.11731	0.2769	0.2493	0.10232
Med-high	0.2726	0.2557	0.07979	0.2327	0.2061	0.08780
High	0.3619	0.2952	0.20268	0.3275	0.2610	0.20512
Total	0.3235	0.2668	0.18063	0.2889	0.2320	0.18277

Table 3: Descriptive statistics of the variables across the industries

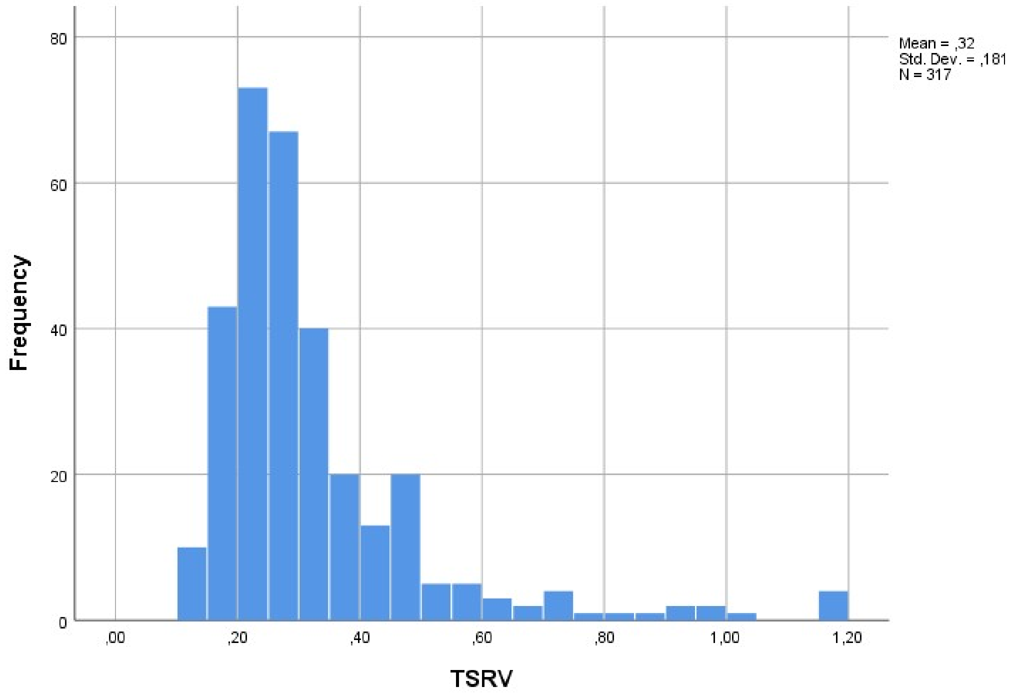

Figure 2: Histogram total stock return volatility (TSRV)

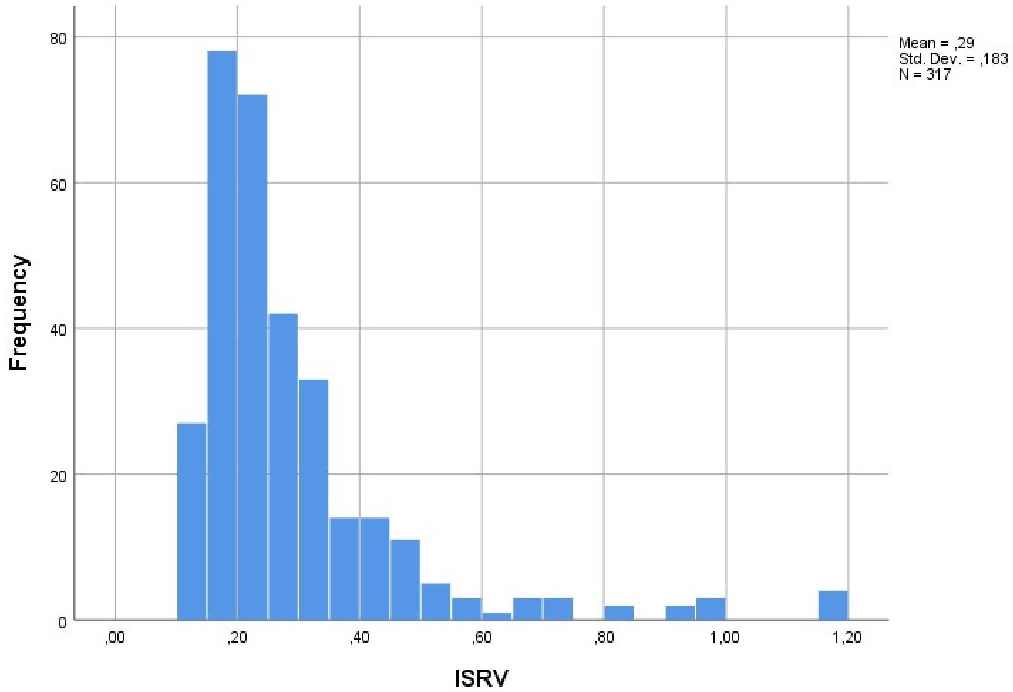

Figure 3: Histogram idiosyncratic stock return volatility (ISRV)

Figure 2 shows the histogram of total stock return volatility (TSRV). Similar results are found in figure 3, which displays the histogram of idiosyncratic stock return volatility (ISRV). Both volatility measures are right-skewed. This is not a strange finding. For example, Gharbi et al. (2014) found similar results. Transforming the variables into logarithms should reduce the skewness and the kurtosis. As a result, the histogram should look much more like a normal distribution. This is confirmed in the numbers (table 4) and in the histogram of the transformed variables (not reported). Skewness reduced from 2.467 (2.662) to 0.907 (0.979) for total (idiosyncratic) stock return volatility. Skewness is a measure of symmetry. Kurtosis reduced from 7.419 (8.442) to 0.931 (1.014) for total (idiosyncratic) stock return volatility. Kurtosis is a measure of how heavily the tails of a distribution differ from the tails of a normal distribution. All in all, there are now four measures of volatility. This results in two additional models:

Model (3): $Ln(TSRV)_{it} = \beta_0 + \beta_1(RDII)_{it} + \beta_2(SIZE)_{it} + \beta_3(LVRG)_{it} + \beta_4(ROA)_{it} + \beta_5(GROW)_{it} + \beta_6(AGE)_{it} + \beta_7(TECH\ Dummy)_{it} + \beta_8(YEAR\ Dummy)_{it} + \varepsilon_{it}$

Model (4): $Ln(ISRV)_{it} = \beta_0 + \beta_1(RDII)_{it} + \beta_2(SIZE)_{it} + \beta_3(LVRG)_{it} + \beta_4(ROA)_{it} + \beta_5(GROW)_{it} + \beta_6(AGE)_{it} + \beta_7(TECH\ Dummy)_{it} + \beta_8(YEAR\ Dummy)_{it} + \varepsilon_{it}$

R&D intensity (RDII) is also right skewed for Dutch tech firms (Appendix 2). This is consistent with the findings on the firm's innovation activities as well, such as Xu and Yan (2014) and Heyden et al. (2015). This can be explained by the fact that most Dutch tech firms do not invest in R&D. As firms cannot invest a negative amount of money on R&D, this is the minimum value for R&D investment intensity. It is impossible to calculate the logarithm of 0, which resulted in the fact that researchers did not transform RDII into a natural logarithm (Xu & Yan, 2014; Heyden et al., 2015). Histograms of all control variables can be found in Appendix 2 as well.

Variable	Mean	Median	Std. dev.	Min.	Max.	Skewness	Kurtosis
TSRV	0.3235	0.2668	0.18063	0.13	1.18	2.467	7.419
Ln(TSRV)	-1.2365	-1.3214	0.43509	-2.04	0.16	0.907	0.931
ISRV	0.2889	0.2320	0.18277	0.11	1.18	2.662	8.442
Ln(ISRV)	-1.3722	-1.4608	0.47334	-2.18	0.16	0.979	1.014

Table 4: Descriptive statistics of the volatility measures

5. Empirical results

In this chapter, the empirical results are presented. The first part of this chapter provides the correlation matrix. The second part focuses on the assumptions of the regression analysis and if these are met or not. The third part shows the results of the regression analysis. In the final part of the empirical results, robustness tests are executed to see if the results from the regression analysis holds.

5.1 Correlation matrix

Table 5 reports the Pearson correlations of the volatility measures, R&D investment intensity and the control variables. This correlation matrix displays the relationship between two variables to identify patterns and potential issues that could affect the results of the regression analysis. The first four columns show the correlation results between the volatility measures and the remaining variables. There is a positive significant relationship between R&D investment intensity and the stock volatility measures. This indicates that stock volatility increases with R&D investment intensity. This supports our hypotheses that R&D investment intensity has an effect on stock risk.

The correlations in table 5 also show that four out of the five control variables have a significant relationship with the volatility measures. Stock volatility is significantly negatively related to size and return on assets. This implies that bigger firms and profitable firms have a lower stock volatility. According to Bhushan (1989), there is more information asymmetry for smaller firms, because financial analysts have a lower incentive to follow the activities of these firms. This may also be the case for less profitable firms, who may get less interest than the most profitable firms. There may arise a problem in the regression analysis if there is multicollinearity between the variables, which means that the variables are substitutes. This will be checked in section 5.2 with the help of the VIF test.

Further, there is a significant positive relationship between the growth opportunities of a firm and the volatility measures. On the other hand, there is a significant negative relationship between age and stock volatility. As younger firms have more growth opportunities than firms in the maturity stage, age should also have a correlation with the growth opportunities. However, there is no relationship between age and growth opportunities. This does not confirm the expectation that older firms have less growth opportunities and also a lower stock volatility. Finally, there is no correlation between leverage and stock volatility. This is in line with the study from Gharbi et al. (2014), who also reported that there was no correlation.

5.2 Regression analysis assumptions

However, there are four assumptions that have to be fulfilled in order to run a regression analysis properly. First of all, the issue of multicollinearity has to be avoided. The VIF test should have a score under 10. Second, linearity of the measured phenomenon. This means that there should be a linear relationship between the dependent and independent variable. This assumption could be checked with the help of a scatter plot. Third, constant variance of the residuals. The scatter plot of the residuals helps to check this assumption. Fourth, normality of the residuals' distribution. This assumption is fulfilled if the histogram of the standardized residual is normally distributed.

	TSRV	Ln(TSRV)	ISRV	Ln(ISRV)	RDII	SIZE	LVRG	ROA	GROW	AGE
TSRV	1									
Ln(TSRV)	0.949**	1								
ISRV	0.976**	0.906**	1							
Ln(ISRV)	0.919**	0.948**	0.941**	1						
RDII	0.324**	0.287**	0.318**	0.278**	1					
SIZE	-0.395**	-0.367**	-0.507**	-0.541**	-0.115*	1				
LVRG	-0.085	-0.073	-0.105	-0.107	-0.089	0.230**	1			
ROA	-0.564**	-0.501**	-0.579**	-0.511**	-0.328**	0.322**	-0.134*	1		
GROW	0.172**	0.127*	0.199**	0.155**	0.133*	-0.242**	0.143*	-0.131*	1	
AGE	-0.267**	-0.313**	-0.245**	-0.312**	-0.070	0.007	-0.049	0.136*	-0.078	1

Table 5: Pearson correlation matrix. Asterisks indicate significance at the 1% (**) and 5% (*) levels in a two-tail test

The first assumption deals with multicollinearity. As there are a lot of significant correlations between the variables in this study, multicollinearity has to be avoided. A common test to check this assumption is the variance inflation factor (VIF) test. A common threshold for this test is that the score should be lower than 10. The results for the VIF test of this study can be found in Appendix 3. The VIF scores are between 1.089 and 1.423, which is considerably lower than the threshold of 10. This means that multicollinearity is not a problem in this study and that this assumption is fulfilled.

The second assumption is the linearity of the measured phenomenon. Scatter plots should show linear relationships between the dependent and independent variables. To have an indication if this assumption is fulfilled, the independent and the significant control variables are plotted against the natural logarithm of total stock return volatility (Ln(TSRV)). The plot against R&D investment intensity (RDII) can be found in figure 4. There is no clear linear relationship between the variables, although the pattern is positive. Even if we remove the RDII values of 0 and above 0.25 (first plot in Appendix 4) and take the square root of these RDIIs to have a nonlinear regression (second plot in Appendix 4), the linearity is still not visible. The other plots against the control variables can also be found in Appendix 4. For size and return on assets, there is a clear negative relationship with stock volatility. The patterns of the relationship for growth opportunities and age are visible, but not as clear as for size and return on assets. However, it causes no problems for this assumption of the regression analysis.

Constant variance of the residuals is the third assumption. The scatter plot of the residuals helps to check this assumption. A residual is the difference between the predicted and observed value. If there are outliers, this could influence the results. This scatter plot is reported in Appendix 5. Although some observations are dispersed, most observations are concentrated in the middle. Therefore, this assumption seems to be fulfilled as well.

Fourth, normality of the residuals' distribution. This assumption is fulfilled if the histogram of the standardized residual is normally distributed. This histogram is reported in Appendix 6. The distribution almost looks like a perfect normal distribution. As a result, it can be said with almost complete certainty that this assumption does not cause any problems. Altogether, all assumptions seem to be fulfilled and the only problem that came up is solved. Therefore, it can be stated that regression analysis is an appropriate method for this study.

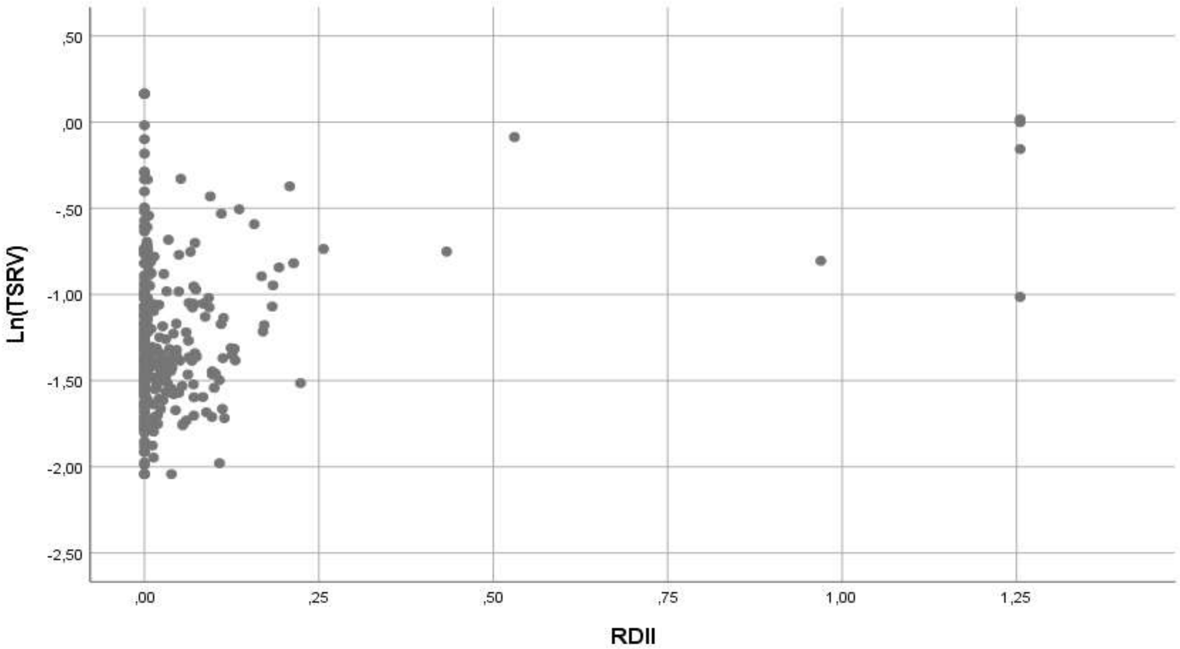

Figure 4: Scatter plot from the logarithm of total stock return volatility (Ln(TSRV)) against R&D investment intensity (RDII)

5.3 OLS regression results

Table 6 reports the OLS regression results to test if R&D investment intensity and stock return volatility are positively related, considering several control variables. There are in total four models, which differ in the measure of stock return volatility. There is a distinction between total stock return volatility (model 1 and 3) and idiosyncratic volatility (model 2 and 4), and between a linear scale (model 1 and 2) and a logarithmic scale (model 3 and 4). This study consists of two hypotheses. First, the OLS regression results from model 1 and 3 will be discussed to test the first hypothesis: *A firm with higher R&D investment intensity tends to have a higher total stock return volatility.* Afterwards, the OLS regression results from model 2 and 4 will be discussed to test the second hypothesis: *A firm with higher R&D investment intensity tends to have a higher idiosyncratic stock return volatility*. In section 5.4, the fixed and random effect regressions will be executed to test if the findings in this section holds.

5.3.1 Hypothesis 1: R&D investment intensity and total stock return volatility

Model 1 and 3 in table 6 reports the OLS regression results to test if there is a relationship between R&D investment intensity and total stock return volatility, considering several control variables. The first hypothesis in this study expects a positive relationship, which means that firms with a higher R&D investment intensity have a higher total stock return volatility. The results show that both measures of total stock return volatility are significant and positively related to R&D investment intensity, which confirms the hypothesis. This is in line with the results from Gharbi et al. (2014), Fung (2006) and Jiang et al. (2020), who document a positive relationship for high-tech French firms and U.S. firms respectively.

The coefficients are similar across both models. In model 1, the coefficient is 0.145 and significant at the 1% level. Furthermore, this effect is economically meaningful, as one standard deviation in R&D investment intensity is associated with a roughly 2.3% increase in the total stock return volatility. This statement is not undermined by a low adjusted R-Squared, because the adjusted R-Squared in this model is 46.1%. In model 3, the coefficient is 0.254 and significant at the 10% level. This finding could be compared to the study of Gharbi et al. (2014), who also conducted a pooled OLS regression where total stock return volatility is measured on a logarithmic scale. Their coefficient for R&D investment intensity is twice as high as the coefficient for the same variable in this study, namely 0.544. The adjusted R-Squared in this model is 45.7%, whereas Gharbi et al. (2014) report an adjusted R-Squared of only 14%. This could explain the different findings, as this model better fits the data.

With regard to the control variables, all of them are significant except for leverage (LVRG) in model 3. In model 1, there is a negative and significant relationship between leverage and total stock return volatility. The other control variables that have a significant and negative relationship with total stock return volatility are size, return on assets and age. Holding all other factors constant, firms that are bigger, more profitable, or older have lower total stock return volatility. On the other hand, there is a significant and positive relationship between growth opportunities and total stock return volatility. This implies that firms in the growth stage, when there are more growth opportunities, have more total stock return volatility.

	(1A) TSRV	(1B) TSRV	(2A) ISRV	(2B) ISRV	(3A) Ln(TSRV)	(3B) Ln(TSRV)	(4A) Ln(ISRV)	(4B) Ln(ISRV)
RDII		0.145***		0.148***		0.254*		0.291**
		(2.621)		(2.759)		(1.904)		(2.139)
SIZE	-0.030***	-0.031***	-0.050***	-0.052***	-0.077***	-0.080***	-0.169***	-0.172***
	(-3.820)	(-4.037)	(-6.655)	(-6.910)	(-4.133)	(-4.278)	(-8.854)	(-9.038)
LVRG	-0.167**	-0.155**	-0.159**	-0.147**	-0.264	-0.242	-0.240	-0.215
	(-2.392)	(-2.233)	(-2.346)	(-2.181)	(-1.570)	(-1.445)	(-1.399)	(-1.260)
ROA	-0.594***	-0.536***	-0.571***	-0.512***	-1.212***	-1.110***	-1.135***	-1.019***
	(-10.352)	(-8.795)	(-10.248)	(-8.659)	(-8.790)	(-7.541)	(-8.068)	(-6.791)
GROW	0.024**	0.023**	0.018*	0.017*	0.052**	0.049**	0.027	0.023
	(2.436)	(2.265)	(1.896)	(1.713)	(2.159)	(2.026)	(1.099)	(0.949)
AGE	-0.031***	-0.032***	-0.029***	-0.029***	-0.093***	-0.094***	-0.105***	-0.106***
	(-4.950)	(-5.095)	(-4.683)	(-4.837)	(-6.114)	(-6.209)	(-6.748)	(-6.865)
Constant	0.689***	0.697***	0.742***	0.751***	-0.251*	-0.236	0.146	0.164
	(11.358)	(11.598)	(12.582)	(12.856)	(-1.724)	(-1.621)	(0.981)	(1.106)
Tech dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.450	0.461	0.492	0.503	0.452	0.457	0.518	0.523
Observations	317	317	317	317	317	317	317	317

Table 6: Effects of R&D investment intensity on stock volatility with OLS regression model. Asterisks indicate significance at the 1% (***), 5% (**) and 10% levels (*). The numbers in the parentheses are t-values.

5.3.2 Hypothesis 2: R&D investment intensity and idiosyncratic stock return volatility

Model 2 and 4 in table 6 reports the OLS regression results to test if there is a relationship between R&D investment intensity and idiosyncratic stock return volatility, considering several control variables. The second hypothesis in this study expects a positive relationship, which means that firms with a higher R&D investment intensity have a higher idiosyncratic stock return volatility. The results show that both measures of idiosyncratic stock return volatility are significant and positively related to R&D investment intensity, which confirms the hypothesis. This is in line with the results from Gharbi et al. (2014) and Mazzucato and Tancioni (2012), who document a positive relationship for high-tech French firms and U.S. firms respectively.

The coefficients are similar across both models. In model 2, the coefficient is 0.148 and significant at the 1% level. Furthermore, this effect is economically meaningful, as one standard deviation in R&D investment intensity is associated with a roughly 2.3% increase in the idiosyncratic stock return volatility. This statement is not undermined by a low adjusted R-Squared, because the adjusted R-Squared in this model is 50.3%. In model 4, the coefficient is 0.291 and significant at the 5% level. This finding could be compared to the study of Gharbi et al. (2014), who also conducted a pooled OLS regression where idiosyncratic stock return volatility is measured on a logarithmic scale. Their coefficient for R&D investment intensity is twice as high as the coefficient for the same variable in this study, namely 0.508. The adjusted R-Squared in this model is 52.3%, whereas Gharbi et al. (2014) report an adjusted R-Squared of only 22.3%. This could explain the different findings, as this model better fits the data.

With regard to the control variables, all of them are significant except for leverage (LVRG) and growth opportunities (GROW) in model 4. In model 2, there is a negative and significant relationship between leverage and idiosyncratic stock return volatility. The other control variables that have a significant and negative relationship with idiosyncratic stock return volatility are size, return on assets and age. Holding all other factors constant, firms that are bigger, more profitable, or older have lower idiosyncratic stock return volatility. On the other hand, there is a significant and positive relationship between growth opportunities and idiosyncratic stock return volatility in model 2. This implies that firms in the growth stage, when there are more growth opportunities, have more idiosyncratic stock return volatility.

5.4 Fixed and random effect regression results

The first robustness test is carried out by using other methods than OLS regression. Fixed effect (FE) and random effect (RE) regression are methods that are used in similar studies where the sample consists of a panel (Gharbi et al., 2014; Mazzucato & Tancioni, 2012). The model for fixed effects allows the constant to differ between firms. This allows firm level factors to influence the relationship. This model assumes that firm-specific effects are correlated with the independent variables. Finally, the model for random effects has a constant which is a random variable. This means that the constant is an error component. Firm-specific effects are assumed to be uncorrelated with the independent variables. To check which method is more appropriate, the Durbin-Wu-Hausman test is conducted. The results that are reported in Appendix 7 show that the FE regression method is preferred over the RE regression method for all models in this study. The results for the FE regression are reported in table 7. This robustness test is carried out to test if the significant and positive relationship between R&D investment intensity and stock return volatility holds or not, considering several control variables.

	(1A) TSRV	(1B) TSRV	(2A) ISRV	(2B) ISRV	(3A) Ln(TSRV)	(3B) Ln(TSRV)	(4A) Ln(ISRV)	(4B) Ln(ISRV)
RDII		-0.162*		-0.169*		-0.541**		-0.593***
		(-1.767)		(-1.908)		(-2.482)		(-2.672)
SIZE	-0.247***	-0.277***	-0.265***	-0.297***	-0.493***	-0.595***	-0.578***	-0.690***
	(-5.092)	(-5.410)	(-5.651)	(-5.990)	(-4.256)	(-4.882)	(-4.889)	(-5.557)
LVRG	-0.308***	-0.293***	-0.344***	-0.329***	-0.187	-0.138	-0.258	-0.203
	(-3.284)	(-3.125)	(-3.789)	(-3.621)	(-0.836)	(-0.617)	(-1.127)	(-0.894)
ROA	-0.192**	-0.202***	-0.166**	-0.176**	-0.327*	-0.360**	-0.249	-0.284
	(-2.516)	(-2.648)	(-2.241)	(-2.384)	(-1.788)	(-1.980)	(-1.332)	(-1.537)
GROW	-0.041***	-0.050***	-0.043***	-0.052***	-0.083**	-0.114***	-0.094***	-0.128***
	(-2.834)	(-3.280)	(-3.075)	(-3.558)	(-2.422)	(-3.150)	(-2.697)	(-3.482)
AGE	-0.039	-0.040	-0.024	-0.024	-0.053	-0.054	-0.007	-0.009
	(-0.865)	(-0.879)	(-0.544)	(-0.558)	(-0.485)	(-0.504)	(-0.062)	(-0.078)
Constant	2.014***	2.193***	2.005***	2.192***	2.148**	2.746***	2.300***	2.955***
	(5.569)	(5.861)	(5.721)	(6.052)	(2.481)	(3.083)	(2.604)	(3.259)
Tech dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.586	0.589	0.620	0.624	0.591	0.599	0.641	0.649
Observations	317	317	317	317	317	317	317	317

Table 7: Effects of R&D investment intensity on stock volatility with fixed effect (FE) regression model. Asterisks indicate significance at the 1% (***), 5% (**) and 10% levels (*). The numbers in the parentheses are t-values.

However, the main findings show conflicting results if we look at the fixed effect (FE) regression in table 7. R&D investment intensity is significant and negatively related to both measures of total stock return volatility (model 1 and 3). The negative and significant sign suggests that an increase in R&D investment intensity reduces the total stock return volatility, and this relationship is influenced by firm-specific effects. The FE model better fits the data than the OLS model. The adjusted R-Squared increased from 46.1% to 58.9% for the linear measure of total stock return volatility and from 45.7% to 59.9% for the logarithmic measure. All in all, the FE regression findings reject the first hypothesis that a firm with higher R&D investment intensity tends to have a higher total stock return volatility.

Similar conflicting results are found for idiosyncratic stock return volatility in model 2 and 4 of table 7. The FE regression results report a significant and negative sign for R&D investment intensity in relation to idiosyncratic stock return volatility, considering the control variables. Again, there are some firm-specific effects that influence this relationship, which could not be explained by the systematic stock return volatility. In these models, the adjusted R-Squared increased from 50.3% to 62.4% for the linear measure of idiosyncratic stock return volatility and from 52.3% to 64.9% for the logarithmic measure. This implies that these models better fit the data. To conclude, the FE regression findings reject the second hypothesis that a firm with higher R&D investment intensity tends to have a higher idiosyncratic stock return volatility.

However, the results for the FE regression are similar to the OLS regression with regard to the control variables for all models. Except that the negative relationship between age and stock return volatility (both measures) is no longer significant. Furthermore, the sign from growth opportunities flipped from significant positive in the OLS regression to significant negative in the FE regression. This suggests that firms in the growth stage, when there are more growth opportunities, are likely to have a lower stock return volatility. This finding is in line with Jiang et al. (2020). The TECH dummy does not affect the results in the regression, except for the intercept in the regression.

5.5 Additional robustness test

As discussed in chapter 4, the histogram of R&D investment intensity is not normally distributed, and this could cause problems (Appendix 2). Especially the outliers could bias the results. Based on the OLS regression, it seems that stocks with a higher R&D investment intensity have a higher stock volatility. Although the FE regression, which considers firm-specific fixed effects, shows that if a firm invests more in R&D than it results in a lower stock volatility. These results seem to contradict each other, but that is not particularly the case. The OLS regression does consider that there is a panel regression, which means that there are multiple observations from one firm. This is the case for FE regression, so each firm has its own intercept and the observations from each firm are compared. If we combine this with the findings from both regression methods, it could be that there is a Simpson's Paradox.

If we focus on the firm-specific level to test what the effect of R&D investment intensity is on stock return volatility, the variable RDII has to be transformed. Therefore, as a robustness test, the variable RDII2 is created. This variable is defined as the R&D expenses in year X for firm Y divided by the R&D expenses in the sample period from firm Y times the number of observations from firm Y. For example, from a firm there are five observations. In a specific year, this firm spends €25 billion with a total of €100 billion over the five observation years. RDII2 for this firm in this specific year would be (25/100)*5=1.25. A value higher than 1 means that this firm spends more on R&D than average in this specific year.

The histogram of the transformed variable is reported in Appendix 8. This histogram looks way more normal distributed than the original variable. As a result, all assumptions for regression analysis are fulfilled. The OLS regression results with the transformed variable can be found in table 8. Note that not all observations are included in this model, but only the observations where a firm spends money on R&D. The result is that there are 170 observations in each model.

The OLS regression results in table 8 confirm the FE regression results. All coefficients are negative and significant. The adjusted R-Squared are not as high as in the FE regression model, but higher than in the original OLS regression model. If a firm invests more in R&D in a specific year, then it has a significant lower stock return volatility. This is the case for total stock return volatility as well as idiosyncratic stock return volatility. As a result, these findings not only reject the hypotheses of this study, but also contradicts the hypotheses that a firm with higher R&D investment intensity tends to have a higher total and idiosyncratic stock return volatility.

With regard to the control variables, most relationships are the same as in the other regression models. However, there are some slight differences. For example, there is no longer a significant negative sign for size related to the total stock return volatility measures. So, bigger firms reduce the level of idiosyncratic stock return volatility but have no effect on total stock return volatility. Further, leverage has a negative significant sign in all models, whereas this was not the case in the other regression models where stock return volatility was measured on a logarithmic scale. Finally, the control variables have the same direction as in the original OLS regression. So, there is a significant positive sign on growth opportunities and a significant negative sign on age. This implies that firms with more growth opportunities and/or younger firms have a higher stock return volatility.

Furthermore, the OLS regression results from table 6 also holds for this sample. An overview of the results is provided in Appendix 9. The coefficients for R&D investment intensity are even higher in each model compared to table 6. So, there is a stronger and significant relationship between R&D investment intensity and stock return volatility for R&D investing firms. This implies that firms with a higher R&D investment intensity tend to have a higher stock return volatility than firms with a lower R&D investment intensity. Again, this is a paradox, because these results do not consider the fact that the data consists of a panel, where one firm has multiple observations.

	(1A) TSRV	(1B) TSRV	(2A) ISRV	(2B) ISRV	(3A) Ln(TSRV)	(3B) Ln(TSRV)	(4A) Ln(ISRV)	(4B) Ln(ISRV)
RDII2		-0.046* (-1.712)		-0.062** (-2.408)		-0.150** (-2.092)		-0.201*** (-2.711)
SIZE	-0.009 (-0.890)	-0.015 (-1.411)	-0.033*** (-3.455)	-0.041*** (-4.107)	-0.007 (-0.252)	-0.026 (-0.932)	-0.113*** (-4.018)	-0.139*** (-4.766)
LVRG	-0.203** (-2.028)	-0.199** (-2.004)	-0.219** (-2.277)	-0.214** (-2.261)	-0.456* (-1.708)	-0.444* (-1.682)	-0.527* (-1.886)	-0.511* (-1.866)
ROA	-0.675*** (-9.670)	-0.650*** (-9.185)	-0.651*** (-9.700)	-0.618*** (-9.162)	-1.401*** (-7.532)	-1.321*** (-7.035)	-1.308*** (-6.713)	-1.201*** (-6.163)
GROW	0.029** (2.166)	0.029** (2.134)	0.025* (1.917)	0.024* (1.883)	0.085** (2.357)	0.083** (2.327)	0.066* (1.742)	0.063* (1.705)
AGE	-0.030*** (-4.207)	-0.027*** (-3.839)	-0.026*** (-3.856)	-0.023*** (-3.397)	-0.102*** (-5.447)	-0.095*** (-5.018)	-0.111*** (-5.669)	-0.101*** (-5.176)
Constant	0.529*** (7.699)	0.597*** (7.554)	0.590*** (8.924)	0.681*** (9.040)	-0.678*** (-3.702)	-0.457** (-2.177)	-0.221 (-1.150)	0.077 (0.354)
Tech dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.543	0.549	0.556	0.569	0.517	0.527	0.526	0.545
Observations	170	170	170	170	170	170	170	170

Table 8: Effects of R&D investment intensity on stock volatility with OLS regression model. Asterisks indicate significance at the 1% (***), 5% (**) and 10% levels (*). The numbers in the parentheses are t-values.

6. Discussion and conclusion

This chapter combines the theories in the literature with the findings in the study to reach a conclusion. The findings will be interpreted into theoretical and practical implications. Furthermore, the limitations of this study are described and recommendations for further research are given.

6.1 Conclusions and implications

There are already several researchers that have investigated the effect of R&D investment intensity on stock return (e.g., Chen et al., 2020; Lu, 2020; Kim & Park, 2020). However, there is little research on the topic of R&D investment intensity and stock risk. The current research that is available, focuses mainly on U.S. firms (Fung, 2006; Jiang et al., 2020; Mazzucato & Tancioni, 2012; Xu, 2006a; Xu, 2006b). Investments in R&D are critical for a firm to survive to distinguish themselves from their competitors in the market and to satisfy customer demand. The successfulness of R&D projects influences future firm performance and brings uncertainty for stock investors. Therefore, this study investigates if R&D investment intensity has an effect on stock return volatility, which is a widely used measure of stock risk (Gharbi et al., 2014).

This paper has used a sample of Dutch listed tech firms between 2011 and 2019 to investigate if R&D intensive tech firms are riskier investments. Regression analysis is used to investigate the link between R&D investment intensity and stock return volatility, while controlling for firm characteristics. The OLS results show that the stock return volatility increases significantly if the R&D investment intensity becomes higher. This could not be explained by systematic volatility, as the results hold for total stock return volatility and idiosyncratic stock return volatility. However, these general findings do not hold when we consider that several observations are related to one firm (i.e., a panel dataset). The FE results show that if a firm decides to increase its R&D investment intensity compared to other years, the stock return volatility decreases significantly. These findings do hold in the OLS regression robustness test, where R&D investment intensity is transformed to a firm-specific variable.

The findings have some implications for theory in this area. The evidence strongly shows that the firms' profitability influences the R&D investment intensity. If the return on assets (a measure of profitability) decreases, then the R&D investment intensity increases significantly (table 5). This implies that underperforming firms are more likely to invest in R&D. These findings are according to the behavioural theory, where firms in hard financial times are more likely to invest in R&D (Greve, 2003). Furthermore, there is a negative and significant relationship between stock return volatility and profitability (ROA). This implies that underperforming firms are also considered as riskier. These findings confirm the risk theory, where firms in hard financial times are more likely to take on more risks (Hu et al., 2019).

However, there might also be another explanation for the above phenomenon. Newly founded firms have to make a lot of investments to start up their firm. As a result, they are less profitable and they do not have a history yet, which makes the stock more volatile. This is supported by the findings, where age is significant and negatively related to stock return volatility. So, younger firms are riskier than mature firms. This could be explained in two ways. First, there is more information asymmetry for smaller firms, because financial analysts have a lower incentive to follow the activities of these firms (Bhushan, 1989). As a result of the discrepancy in the availability of information, the increasing uncertainty could result in more risk for the stock investor (Giambona et al., 2018). This implies that younger firms have more information asymmetry, which results in more stock return volatility.

The other explanation is related to the absorptive capacity theory. The ability to learn from the environment and make financial benefits out of this could reduce the stock return volatility. As young firms have no experience, they may not be able to learn from their own mistakes (knowledge spillovers). In line with this, Fung (2006) expected a negative relationship between knowledge spillovers and stock return volatility. As a result, mature firms are more capable of learning from inside (mistakes) and outside (environment), which reduces the stock return volatility. This explanation gives support for the absorptive capacity theory.

Another theory that is discussed in this study is the inertia theory. This theory assumes that high firm performance suppresses R&D investment intensity more than low firm performance increases them (Greve, 2003). The reason for this is that past knowledge and past experience replaces the need for new knowledge (Jiang et al., 2018). Although this cannot be confirmed or rejected by the findings, it seems that it is not the case. The FE regression results showed that if a firm decided to increase its R&D investment intensity, its stock return volatility decreases. Xu (2006a) assumed that the relationship between R&D investment intensity and stock return volatility is affected by the R&D stage and success rate. A new R&D stage may require an increase in R&D expenses. For example, a prototype has to be built. The further the stage, the lower the uncertainty and the higher the success rate. This might explain why stock return volatility decreases if R&D investment intensity increases. However, this is not in line with the inertia theory, because this theory assumes good performing firms to suppress the R&D investment intensity.

The results have practical implications for stock investors as the aim of this study is to provide an answer to stockholders if R&D intensive tech firms are riskier investments. The general results showed that firms that have a higher R&D investment intensity have a higher stock return volatility. This is in line with other studies, such as Gharbi et al. (2014), Fung (2006) and Jiang et al. (2020). This implies that these stocks are riskier and should be avoided. However, as R&D investment intensity increases, so does the stock return (e.g., Chen et al., 2020; Lu, 2020; Kim & Park, 2020). All in all, there is a trade-off between risk and return. Risk-averse stock investors are likely to buy stock from firms that do not invest in R&D as they are safer. However, the downside is that these stocks have a lower return than R&D stocks.

The second practical implication is for the owners/management from the firm. As a firm decides to increase its R&D investment intensity, the stock return volatility decreases. This could be explained by the fact that the firm reached a new stage in the R&D project. This could give a positive signal to stock investors and, as a result, makes the stock less risky. The management should provide information that reduces the uncertainty about the product's success probabilities and the expected profits.

6.2 Limitations and recommendations

The results of this paper suggest some important areas for future research. First, the results are based on R&D investment intensity, which is an input measure of R&D (Mazzucato & Tancioni, 2012). Future work may consider output measures of R&D, such as patents, or other measures that identify in which stage of the R&D project a firm is. When data with output variables become available, an important application would be to consider to which extent R&D projects are successfully commercialized. Second, researchers may want to test these findings and include data about the information that is provided to stockholders. For example, how many times does a firm report on their R&D project and is this information positive or negative. As R&D is related to uncertainty, providing information could influence the results.

An important limitation of this study is that it is only limited to stock return volatility and the beta as measures of stock risk. Future work may also consider other measures, such as down-side risk. Stock volatility measures the sensitivity of a stock and how stable it is, whereas down-side risk measures the potential loss of a stock. It would be valuable to consider if the results hold if there is another measure of stock risk. Another useful extension would also be to consider whether the results are only specific for the Netherlands or are more general. As this is only the second research on this topic that considered a sample outside the U.S., it could be worth testing the results for all of Europe instead of one country. Comparative work would help investigate these issues.

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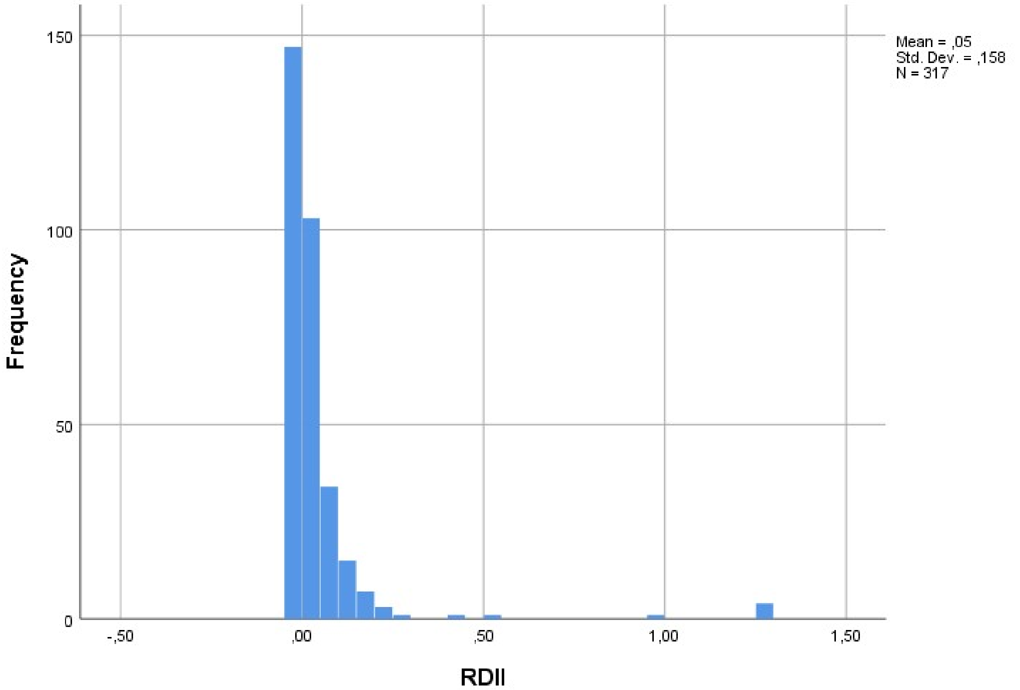
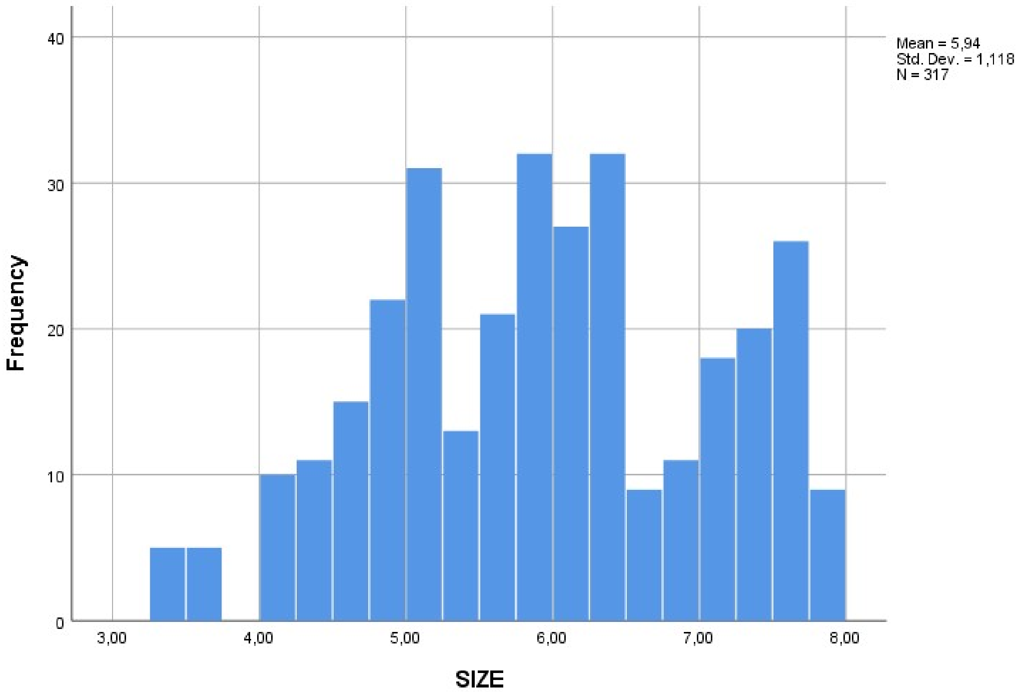
Appendices

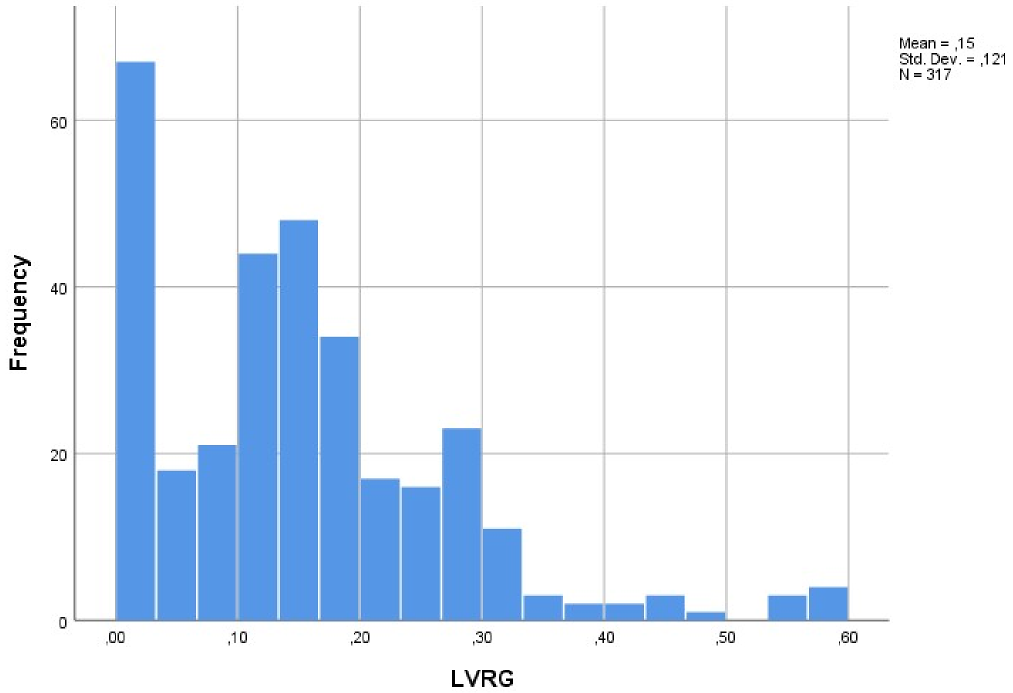
Appendix 1: List of sample firms with their NACE Rev. 2 classification

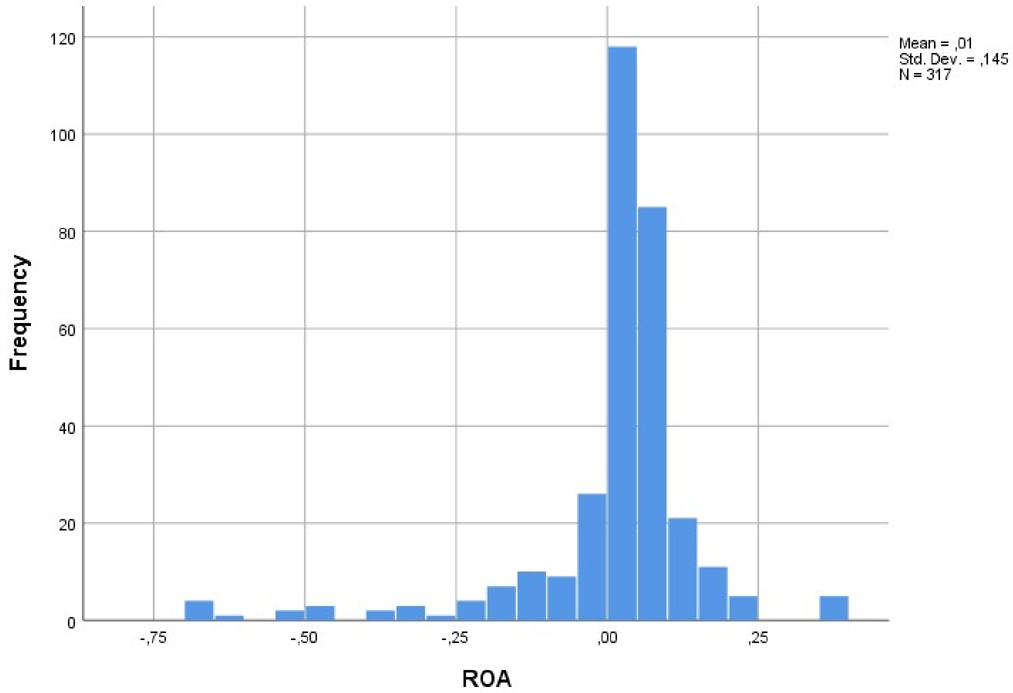
Company Name	Classification	Core code	Industry
AALBERTS NV	28	2814	Medium-high-technology
ACCELL GROUP	30	3091	Medium-high-technology
ACCSYS	32	3299	Low technology
AKZO NOBEL	21	2120	High technology
ALFEN	27	2790	Medium-high-technology
AMG	19	1910	Medium-low-technology
APERAM	24	2420	Medium-low-technology
ARCELORMITTAL SA	24	2452	Medium-low-technology
ASM INTERNATIONAL	26	2611	High technology
ASML HOLDING	26	2611	High technology
AVANTIUM	20	2059	Medium-high-technology
BE Semiconductor	26	2611	High technology
BETER BED	31	3109	Low technology
COCA-COLA EUROPEAN	11	1107	Low technology
CORBION	10	1082	Low technology
DSM KON	20	2059	Medium-high-technology
EASE2PAY NV	18	1820	Low technology
HEINEKEN	11	1105	Low technology
HEINEKEN HOLDING	11	1105	Low technology
HOLLAND COLOURS	20	2030	Medium-high-technology
HUNTER DOUGLAS	16	1629	Low technology
HYDRATEC	22	2223	Medium-low-technology
IEX GROUP NV	10	1091	Low technology
IMCD	20	2059	Medium-high-technology
KENDRION	22	2229	Medium-low-technology
KIADIS	21	2120	High technology
LUCAS BOLS	11	1101	Low technology
NEDAP	26	2611	High technology
NEWAYS ELECTRONICS	26	2611	High technology
OCI	20	2015	Medium-high-technology
PHARMING GROUP	21	2120	High technology
PHILIPS KON	27	2751	Medium-high-technology
PORCELEYNE FLES	23	2341	Medium-low-technology
ROODMICROTEC	26	2611	High technology
SAINT GOBAIN	23	2311	Medium-low-technology
SIF HOLDING	28	2899	Medium-high-technology
SIGNIFY NV	27	2740	Medium-high-technology
TKH GROUP	24	2434	Medium-low-technology
TOMTOM	26	2630	High technology
VALUE8	26	2611	High technology
TEN CATE BV	13	1399	Low technology
NUTRECO NV	10	1013	Low technology
OCE HOLDING BV	28	2823	Medium-high-technology
TELEGRAAF MEDIA GROEP BV	18	1811	Low technology

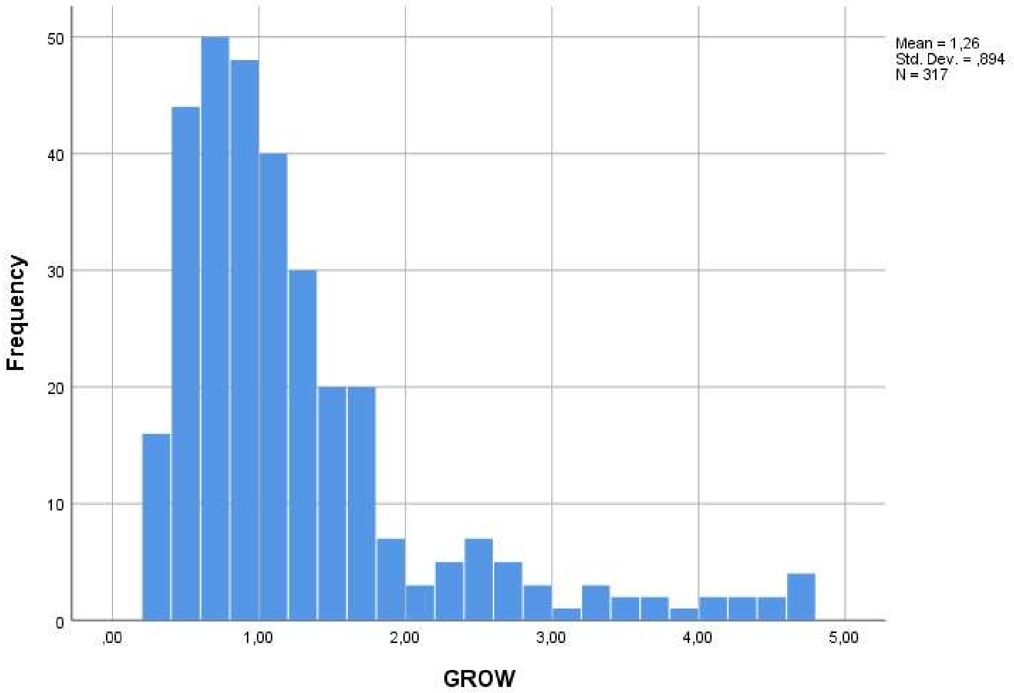
Appendix 2: Histogram of all variables

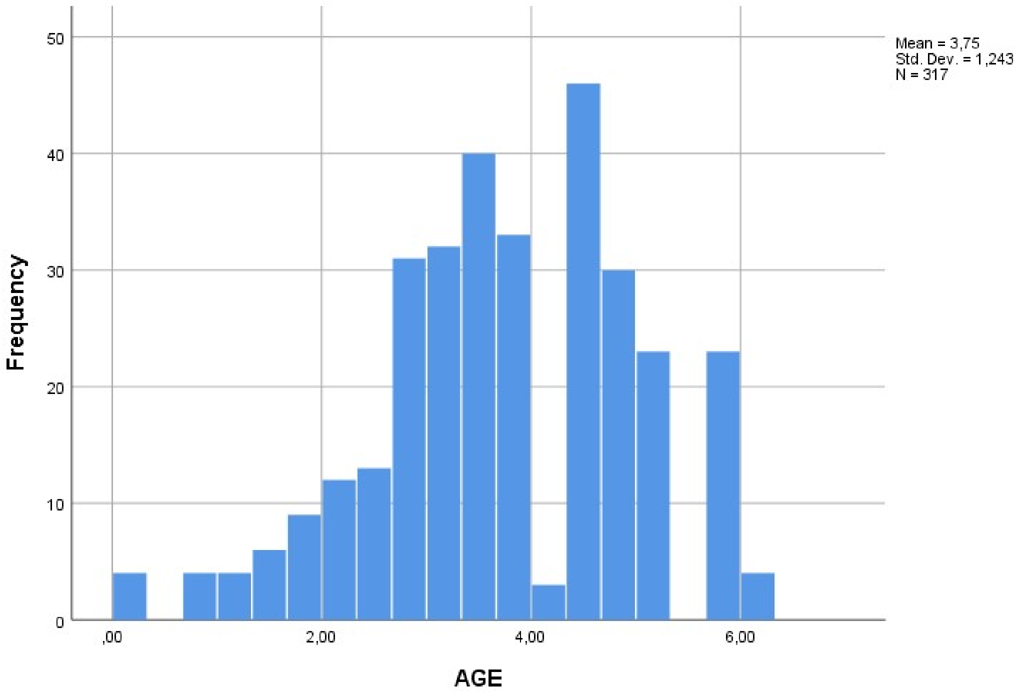





Mean = ,15
Std. Dev. = ,121
N = 317
Frequency
0
20
40
60
,00
,10
,20
,30
,40
,50
,60
LVRG


Mean = ,01
Std. Dev. = ,145
N = 317
Frequency
0
20
40
60
80
100
120
-,75
-,50
-,25
,00
,25
ROA

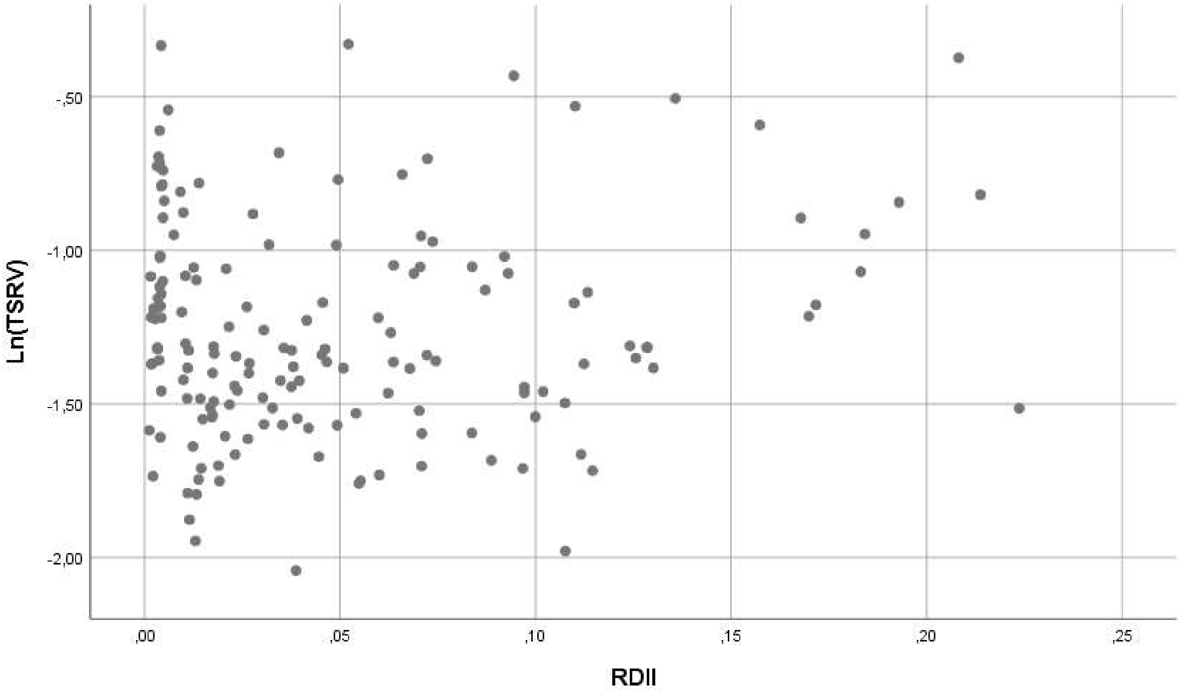

Mean = 1,26
Std. Dev. = ,894
N = 317
Frequency
GROW

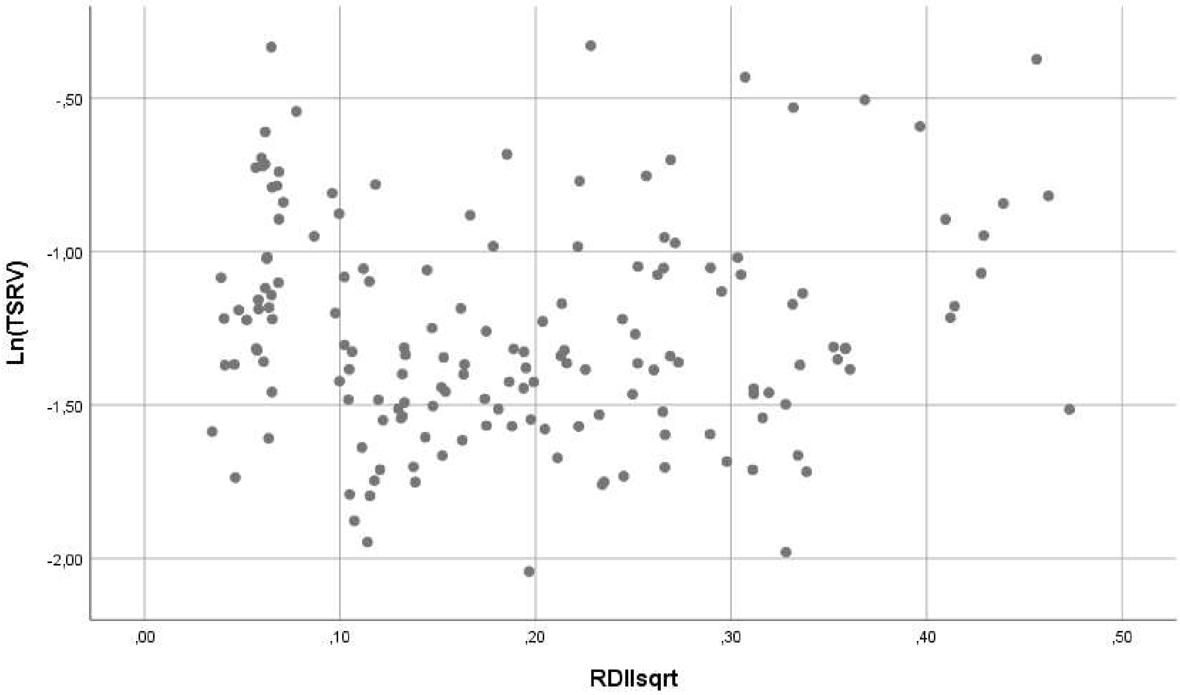

Mean = 3,75
Std. Dev. = 1,243
N = 317
Frequency
AGE

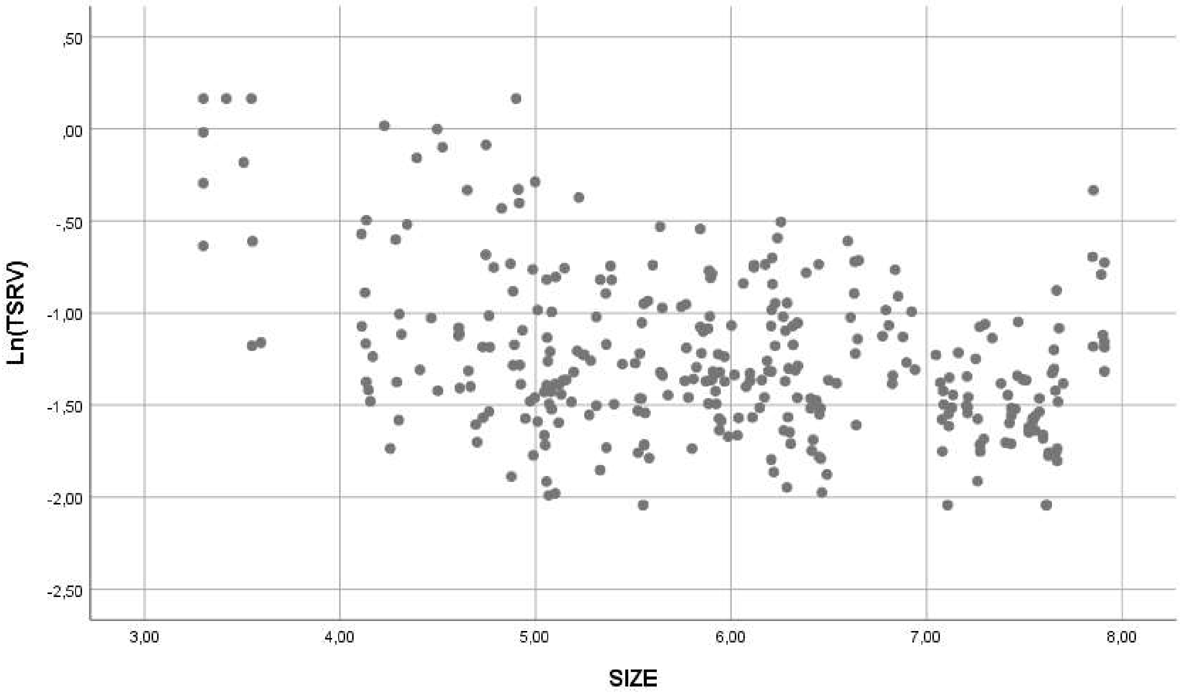
Appendix 3: Variance Inflation Factor (VIF) Test

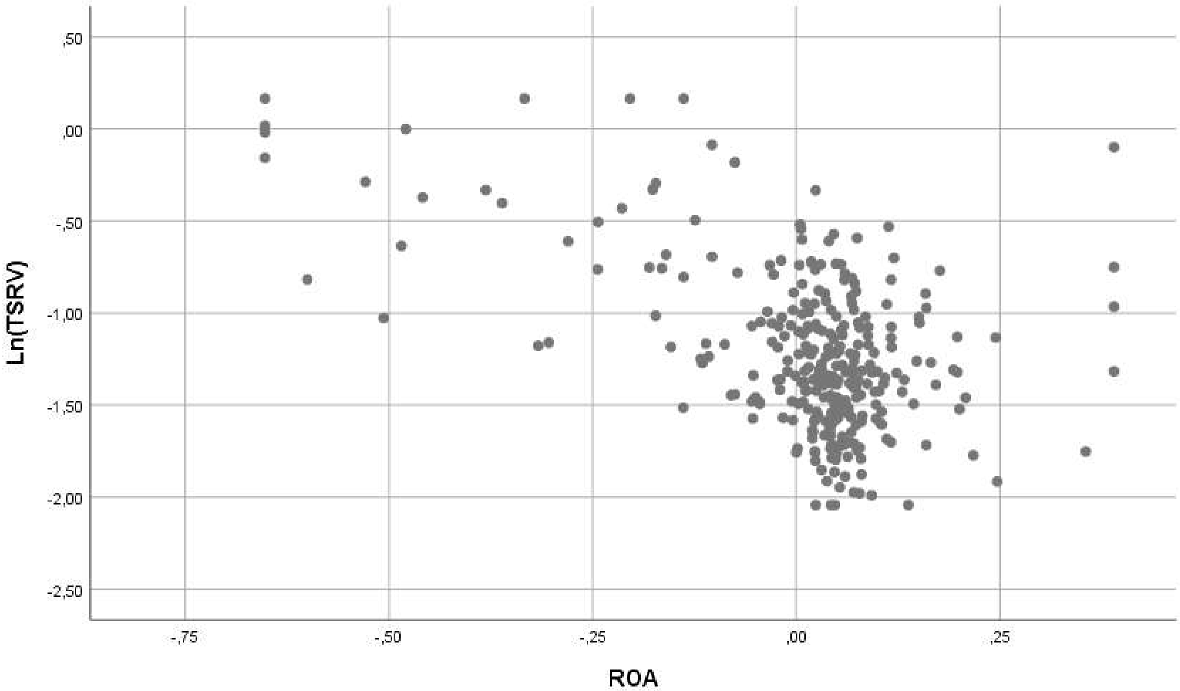
Variable	VIF score
RDII	1.362
SIZE	1.334
LVRG	1.271
ROA	1.399
GROW	1.423
AGE	1.089

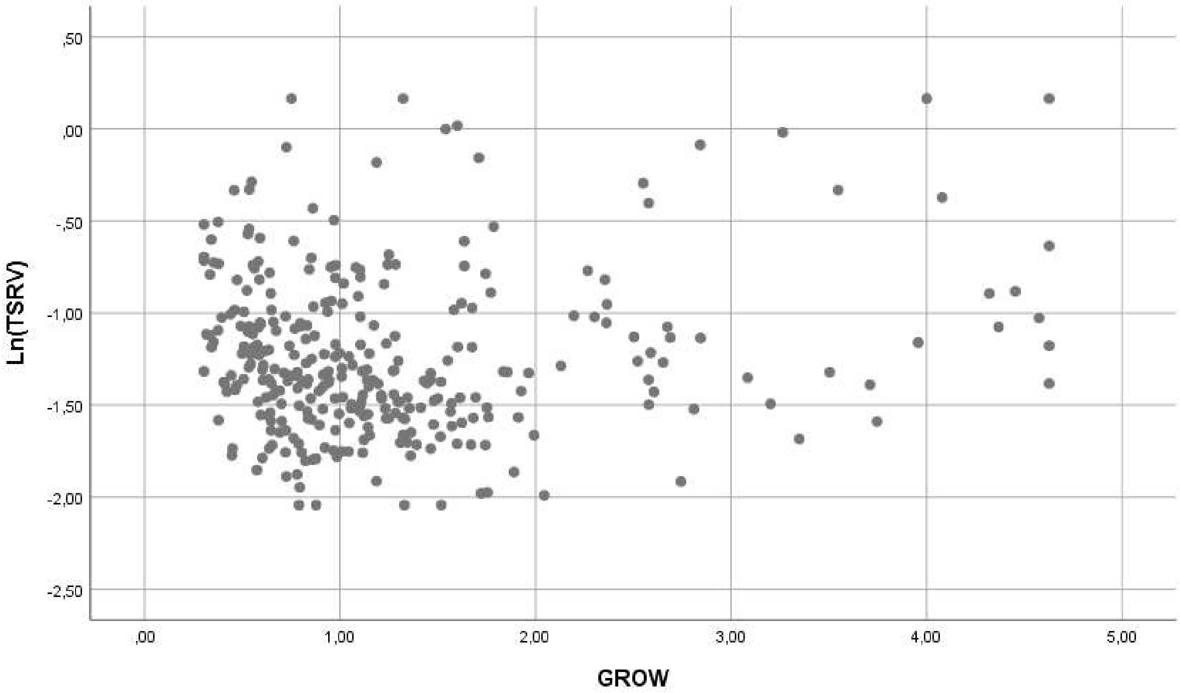
Appendix 4: Scatter plots stock volatility against other variables



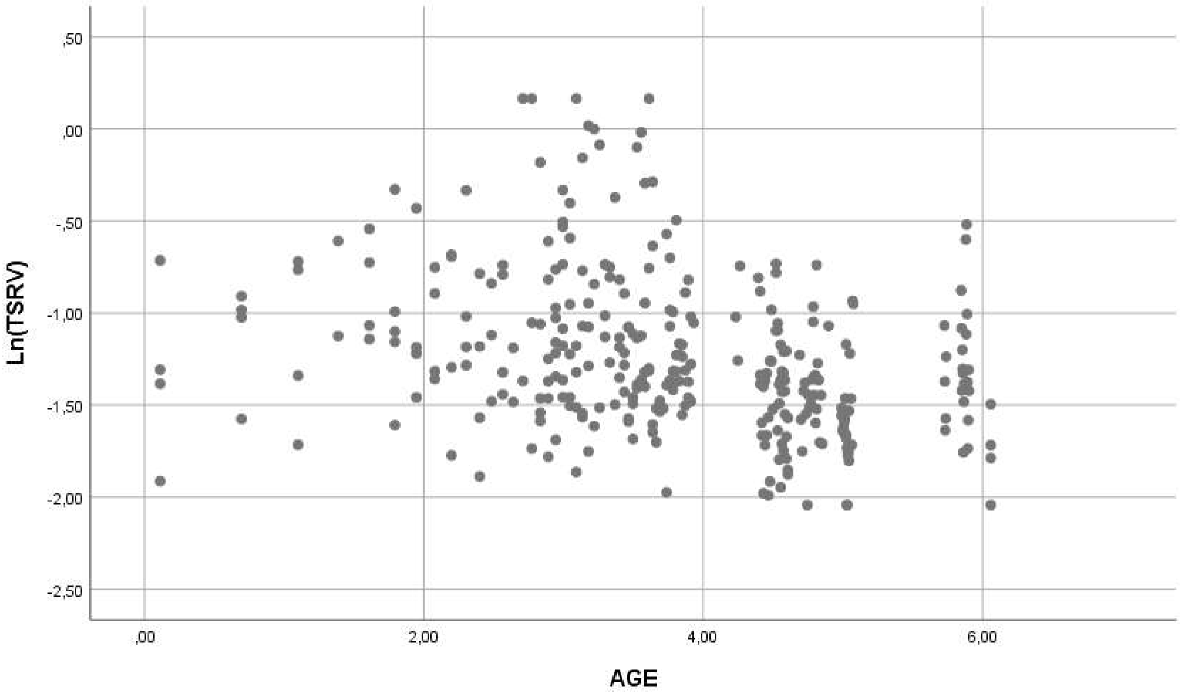



Ln(TSRV)
,50
,00
-,50
-1,00
-1,50
-2,00
-2,50
3,00
4,00
5,00
6,00
7,00
8,00
SIZE


Ln(TSRV)
,50
,00
-,50
-1,00
-1,50
-2,00
-2,50
-,75
-,50
-,25
,00
,25
ROA

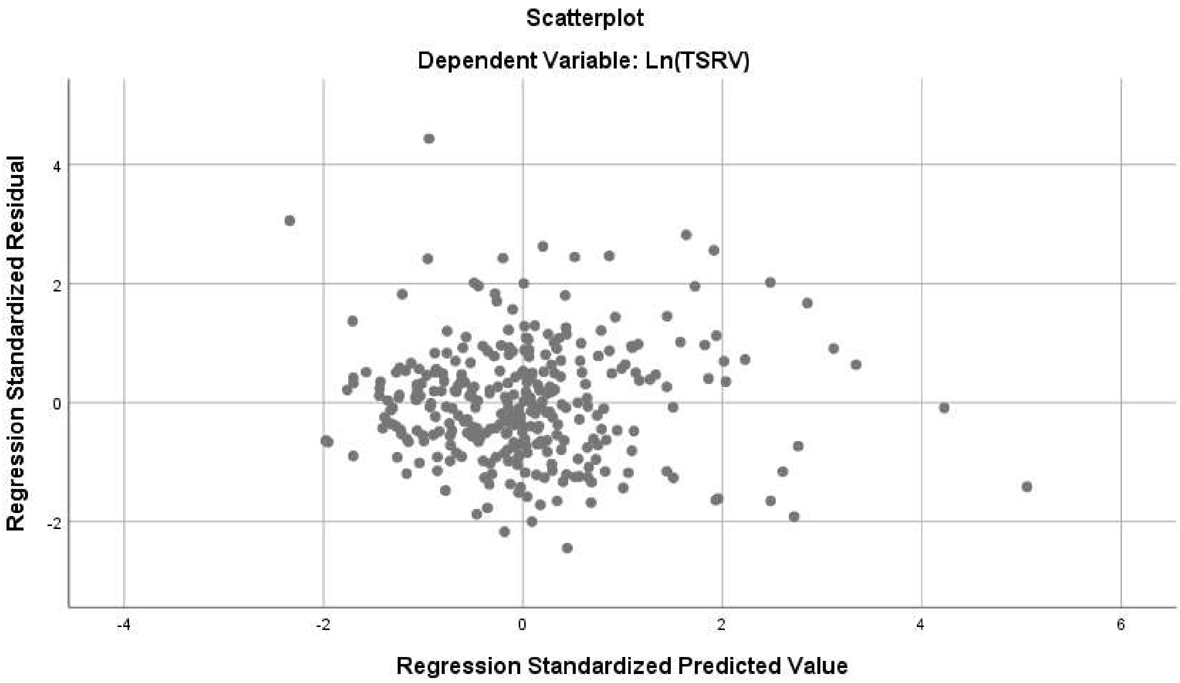


Ln(TSRV)
GROW
,50
,00
-,50
-1,00
-1,50
-2,00
-2,50
,00
1,00
2,00
3,00
4,00
5,00

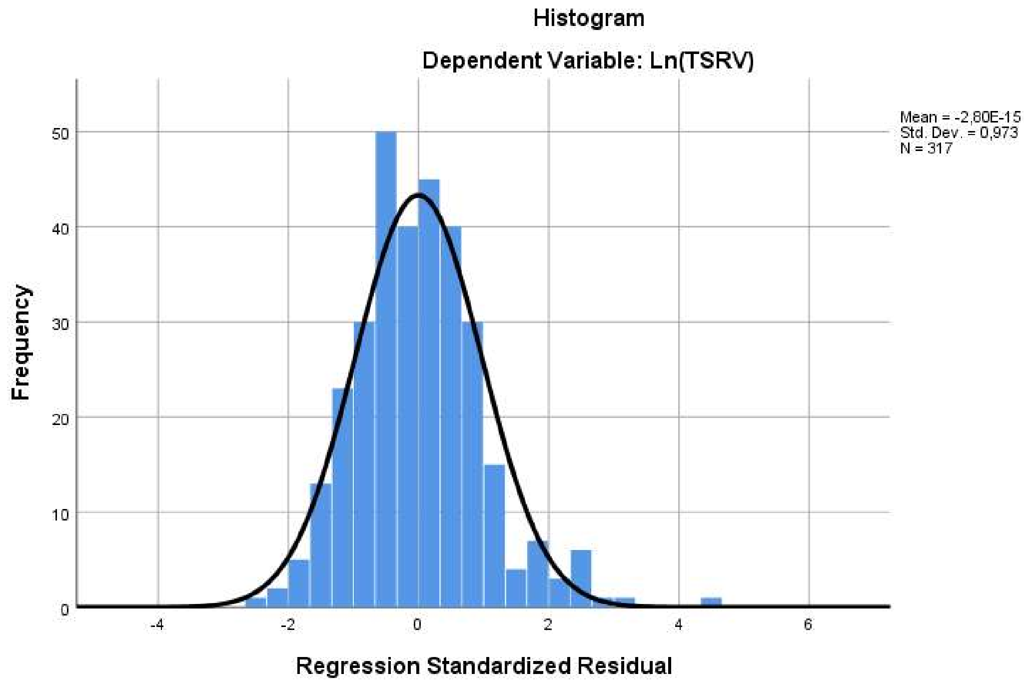


Ln(TSRV)
AGE
,50
,00
-,50
-1,00
-1,50
-2,00
-2,50
,00
2,00
4,00
6,00

Appendix 5: Constant variance of the residuals



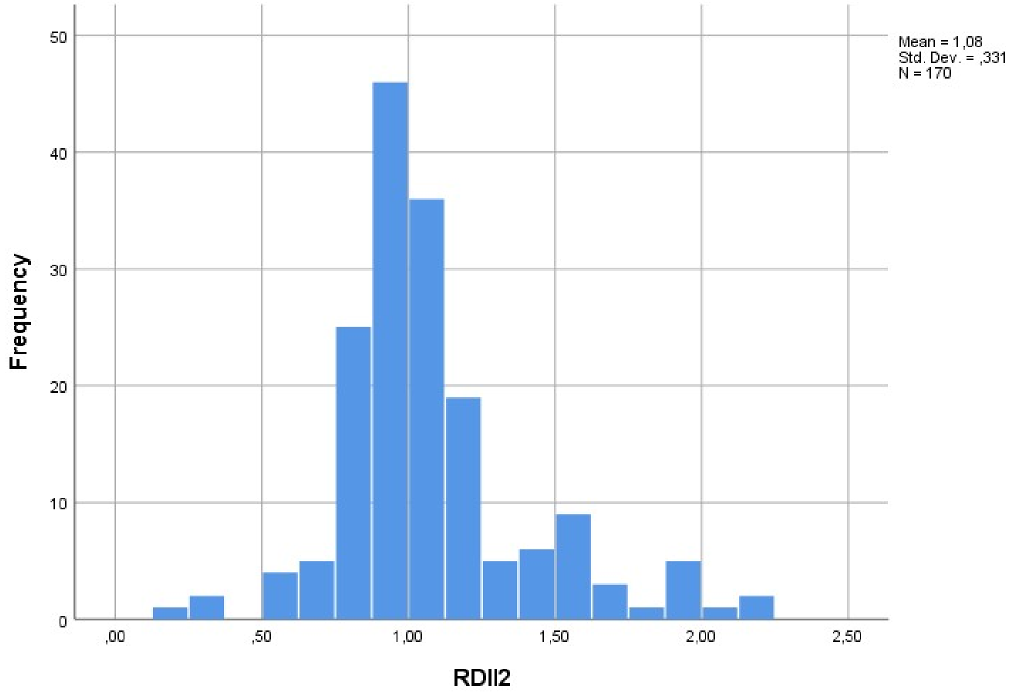
Appendix 6: Normality of the residuals' distribution



Appendix 7: Durbin-Wu-Hausman Test

	Chi-squared	P-value	Conclusion
Model 1	68.892	<0.001	FE > RE
Model 2	82.642	<0.001	FE > RE
Model 3	48.388	0.006	FE > RE
Model 4	49.455	0.004	FE > RE

Appendix 8: Histogram of transformed R&D intensity variable



Appendix 9: Effects of R&D investment intensity on stock volatility with OLS regression model for R&D investing firms

	(1A) TSRV	(1B) TSRV	(2A) ISRV	(2B) ISRV	(3A) Ln(TSRV)	(3B) Ln(TSRV)	(4A) Ln(ISRV)	(4B) Ln(ISRV)
RDII		0.224***		0.229***		0.407**		0.456***
		(3.828)		(4.104)		(2.551)		(2.736)
SIZE	-0.009	0.001	-0.033***	-0.023**	-0.007	0.011	-0.113***	-0.093***
	(-0.890)	(0.102)	(-3.455)	(-2.433)	(-0.252)	(0.418)	(-4.018)	(-3.247)
LVRG	-0.203**	-0.198**	-0.219**	-0.214**	-0.456*	-0.446*	-0.527*	-0.516*
	(-2.028)	(-2.063)	(-2.277)	(-2.334)	(-1.708)	(-1.703)	(-1.886)	(-1.886)
ROA	-0.675***	-0.453***	-0.651***	-0.424***	-1.401***	-0.997***	-1.308***	-0.856***
	(-9.670)	(-5.127)	(-9.700)	(-5.020)	(-7.532)	(-4.128)	(-6.713)	(-3.393)
GROW	0.029**	0.031**	0.025*	0.026**	0.085**	0.088**	0.066*	0.069*
	(2.166)	(2.379)	(1.917)	(2.141)	(2.357)	(2.478)	(1.742)	(1.863)
AGE	-0.030***	-0.035***	-0.026***	-0.032***	-0.102***	-0.112***	-0.111***	-0.122***
	(-4.207)	(-5.074)	(-3.856)	(-4.797)	(-5.447)	(-5.945)	(-5.669)	(-6.221)
Constant	0.529***	0.495***	0.590***	0.554***	-0.678***	-0.740***	-0.221	-0.290
	(7.699)	(7.448)	(8.924)	(8.737)	(-3.702)	(-4.077)	(-1.150)	(-1.531)
Tech dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.543	0.581	0.556	0.597	0.517	0.534	0.526	0.545
Observations	170	170	170	170	170	170	170	170

Asterisks indicate significance at the 1% (***), 5% (**) and 10% levels (*). The numbers in the parentheses are t-values.