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From R&D to Riches: Assessing the Financial Impact of R&D Intensity in the US Semiconductor Industry

Bachelor Thesis: Financial Economics

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ABSTRACT

The aim of this thesis is to understand the extent to which R&D investment intensity affects firm financial performance in the context of American semiconductor firms. By employing financial statement data on 151 publicly listed US semiconductor firms, I conducted a panel data analysis using fixed and random effects regressions to assess the relationship. I find that the one and two-period lags of R&D investment intensity have a positive effect on a firm's economic value added, a negative effect on their gross profit margins, and an insignificant effect on their Tobin *q* ratio. The results provide useful information for semiconductor firm management, shareholders, and American policymakers in making decisions about allocating funds towards R&D expenditures. Such decisions play a critical role in semiconductor product reliability and performance, and the company's financial success.

Keywords: R&D investment intensity, Semiconductors, Economic Value Added, Gross Profit Margin, Tobin's *Q*

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CHAPTER 1 Introduction

The US semiconductor industry is entering a new era, backed by the CHIPS and Science Act of 2022, a government bill that provides 52 billion USD in funding to firms to secure the future of American semiconductor research and development (R&D) and manufacturing. Such government spending is expected to drive growth and long-term financial performance in the industry. The effect of R&D investment on financial outcomes has been studied extensively in academic research so far. Previous research by Lantz and Sahut (2005) states that technological firms' growth is based on the exploitation of innovative products and services thus forcing them to strongly invest in R&D. They justify their research by explaining that R&D expenditures publicise the strategic positioning of firms, which can worsen their financial performance. By performing a regression, the authors find evidence that publicly listed European technological firms that invest heavily in R&D have significantly worse financial performances than firms with a lower investment intensity. The academic community findings offer some debate on this topic as they argue that R&D investment intensity and profitability are positively correlated, however, the results are derived from a sample of firms across multiple industries, not just technology, which may have led to different conclusions (for a review, see VanderPal, 2015). In 2021, US semiconductor companies invested one-fifth of their annual revenues, amounting to 50.2 billion USD, in R&D (Semiconductor Industry Association, 2022). Further research on this topic is relevant as it would aid industry leaders and policymakers in making informed decisions about allocating billions of USD most effectively.

Literature on the topic examines how internal R&D activities, knowledge transfer, and financial performance affect one another in the Taiwanese semiconductor industry, with human capital being the mediating variable. Chen and Wu (2020) conclude that R&D intensity improves the commercial viability of companies, and in the long run creates a competitive edge, improves profitability, and generates intangible assets through innovation and goodwill. My study explores how varying levels of R&D intensity can lead to different financial outcomes in the US semiconductor industry. The motivation behind studying the relationship in a different setting stems from numerous reasons, such as how the US industry has traditionally been the leader in semiconductor R&D, but trends have changed and Taiwanese firms such as TSMC have increased their R&D expenses by an average of 21.53% increase each year in the past 3 years (MacroTrends, 2023). Furthermore, US semiconductor firms account for 50% of the global market share in the industry (Semiconductor Companies Market Share 2022 | Statista, 2023). The differing industry characteristics in both countries provide valuable insights to discuss. To underscore the significance of this research, I refer to a paper by Nin-Pratt (2021), which highlights how different countries use R&D intensity metrics to monitor progress towards development and policy objectives, and to also evaluate set R&D investment targets.

I investigate the effect of R&D investment intensity on financial performance following a similar methodology to Chen and Wu (2020). I expect to find evidence in favour of their findings, even though our study differentiates itself by focusing on a different country of interest, dropping the role of human capital as a mediating variable, and using other measures of financial performance. I will analyse the impact of R&D investment intensity on the financial performance of semiconductor firms over a period of 10 years in the US. Examining the US as a country of interest will let me draw conclusions on returns from R&D investment for companies in the same industry across different countries, while also permitting the inspection of the impact of government bills such as the CHIPS and Science Act of 2022 on these returns. This is the main motivation behind studying the relationship; if I find similar results to Chen and Wu, it will provide evidence in favour of the fact there are other factors besides R&D investment intensity that differentiate the financial performance of semiconductor firms. Additionally, focusing solely on the direct relationship between R&D investment intensity and financial performance will let me determine the extent to which R&D investment intensity dictates the financial well-being of firms. This brings us to my research question:

How does R&D investment intensity affect the financial performance of companies?

To answer the research question, I will perform a quantitative analysis of the data by employing the use of a statistical regression similar to the one produced by Chen and Wu (2020). R&D investment intensity, the primary independent variable of interest, is calculated as the ratio of a firm's R&D investment to its revenue (CODED - Eurostat's Concepts and Definitions Database, 2022). The financial performance metrics which serve as my dependent variables include economic value added (EVA), gross profit margin, and Tobin's q. All monetary variables are reported in million USD. To ensure accuracy and improve the internal validity of the study, I will include additional control variables in the analysis. My study samples the 151 semiconductor companies listed from 2012-2022 US stock exchanges, including the NYSE, NASDAQ, and OTC, as found on Wharton Research Data Services (2023). Using WRDS I also extract panel data on R&D investment intensity by taking the R&D expenses and revenues for each company in the period 2012-2022. The financial data for each company, including additional firm-specific control variables such as leverage, liquidity, capital intensity, and firm size will be sourced from WRDS as well.

Based on the semiconductor industry's research-driven nature and significant capital investments in firms, I hypothesize that higher R&D investment intensity has a positive and significant effect on a firm's financial performance. I expect that large capital investments and increased intensity will ensure future long-term growth, technological advancement, and a competitive edge for companies. The effect of R&D investment intensity should be visible in the positive coefficient of the variable and its statistical significance. The findings of my analysis will provide valuable insights into the financial outcomes of different levels of R&D intensity for firms in the US semiconductor industry, how government policies have shaped these outcomes, and how they differ across countries. Furthermore, the results offer an understanding for policymakers on how they can more effectively regulate investments in the industry. Although I expect the research to add to the existing literature on the topic, I do not consider the effects of investment intensity on non-financial variables such as environmental sustainability or level of innovation, which could be discussed in future studies on the topic.

CHAPTER 2 Theoretical Framework

The relationship between R&D and financial performance has been extensively studied, particularly in the past 50 years, as companies and their stakeholders race to reap monetary benefits of investments in innovation, and academic researchers alongside wish to understand the effects, if any, of these R&D expenditures on firm financial performance. In this chapter of my paper, I will perform a review of the existing literature on the topic. The discussion points of this chapter include the conceptualisation of the topics, how they have been studied before, and how they relate to each other. Financial performance will be reviewed first, followed by R&D investment intensity, after which I will examine at the relationship between them.

2.1 [Criteria for Evaluating the Financial Performance of Firms]

Measuring financial performance is a crucial aspect of managing a company, as it enables a firm to quantify its own financial health. Financial performance numbers are presented in different forms, usually as financial metrics or ratios, depending on how a company wishes to showcase this information. Financial performance metrics such as return on investment (ROI) suffer from inherent defects that may cause dysfunctional decision-making on the part of managers (Otley, 1999). Venanzi (2011) provides further evidence on the defects of ROI, namely how accounting-based measures of return fail to consider the cost of invested capital, so maximising returns or earnings does not imply maximising shareholder value. As a result, it is better for our analysis to include other variables that capture shareholder value maximisation with a more reliable estimate. Additionally, we need a measure of financial performance that encapsulates value created by R&D.

Economic value-added (EVA™)[1] measures residual income, or net operating profits less a charge for the opportunity cost of invested capital (Worthington & West, 2001). EVA™ essentially measures value created above the cost of capital for a firm, or above the required rate of return by shareholders, so it is a fine measure of the economic profitability of a company's operations. Another variable that measures value created by the firm is gross profit margin, which measures the remaining percentage of the sale if a company has paid for its goods (Nariswari & Nugraha, 2020). Having a higher gross profit margin means companies can keep their costs under control to create profit. Tobin's q is defined as the ratio of market value to asset replacement cost of the firm (Smirlock et al., 1984; Lindenberg & Ross, 1981). It measures the relationship between the intrinsic value of an asset and its market valuation. Since R&D creates intangible assets that can contribute to future performance (Shin et al., 2017), it can be argued that higher levels of R&D spending should lead to higher Tobin's q values (Connolly & Hirschey, 2005). These are the three variables which serve as measures of financial performance in this paper.

[1] EVA™ is a trademark of the Stern Stewart Corporation.

Financial performance is a measure of how well companies utilise assets to generate revenue. It is conducted periodically to help investors formulate their expectations about the future earning potential of a firm (Venanzi, 2011). This report analyses the financial performance of American semiconductor firms. The semiconductor market is the textbook example of how Schumpeter's 'perennial gale of creative destruction' (innovation) has played a major role in the development and growth of the industry (Malerba, 1985). The American resurgence of semiconductor firms is attributed to the improvement of organisational innovation and specialisation, as these firms took advantage of their global manufacturing capabilities and structural advantages (Langlois & Steinmueller, 2000), so understanding the financial performance of these firms is a crucial part of continuing this resurgence.

One of the first books to discuss financial performance is The Modern Corporation and Private Property by Adolf Berle and Gardiner Means from 1932. The seminal literature on the topic is the first published literature to discuss the separation of ownership and control in a corporation, but it goes further and underscores the significance and effect of this separation on corporate performance. The authors argue that profits are an essential part of the corporate system and using corporate power to serve stockholders is no longer likely to serve public interest, yet no criteria of good corporate performance has been identified (Berle & Means, 1932). The essence of Berle and Means' argument is that companies have grown their economic power on scales previously unknown, and as a result have lost sight of a clear definition on what good corporate performance constitutes. The authors make the case that criteria for evaluating financial performance have got to be developed and they studied this topic by looking into the structure and operations of large corporations. The book provides arguments in favour of ROI and return on equity as two good criteria, yet these two metrics will not serve our purpose in this paper, as mentioned earlier. EVA™, gross profit margin, and Tobin's *q* are the three criteria we concern ourselves with. These variables do not measure how companies serve public interest, but rather shareholder value creation and R&D value creation, which better serve the aim of my paper.

2.2 [R&D Investment Intensity]

Corporate R&D investment is increasingly capturing the attention of the academic debate since it is of crucial importance to translate novel technologies into organisational processes, products, and services (Ginesti et al., 2021; Almor et al., 2022). Alongside this, there is a growing stream of studies analysing R&D investment intensity, specifically in the topics of agriculture, high-technology firms, and manufacturing (Shen & Lin, 2020; Nin-Pratt, 2021; Zhu & Huang, 2012). R&D investment intensity is defined as R&D investment as a proportion of revenue (Stock et al., 2001; Cohen & Levinthal, 1990). Deriving R&D intensity figures gives us a sense of the degree to which firms are investing in innovation, a key driver of growth, specifically in globally competitive high-tech manufacturing industries. The concept of technological innovation refers to any incremental or radical change in technology embodied in product and process (Sher & Yang, 2005). R&D intensity is also a key indicator used to monitor resources devoted to science and technology worldwide (CODED - Eurostat's Concepts and Definitions Database, 2022). In this paper I will present a figure showcasing the trend in the R&D investment intensity of US semiconductor firms, which will help better understand how this dynamic industry has been changing in the past.

The semiconductor industry is characterised by first mover advantages. Firms that achieve a competitive advantage in the industry do so by either by speeding up the manufacturing process or improving on the product design. Semiconductor process development present numerous challenges, such as grappling with a complex production system of >500 steps, but also with the fact that new manufacturing process generations involve changes in almost all processing activities (West & Iansiti, 2003). According to Chen & Li (1999), successful product development involves effective R&D investments. The literature tells us that efficient R&D spending is the key that opens the lock of semiconductor business success. This is confirmed in Griliches' (1987) seminal paper where the author finds significant evidence in favour of a positive effect between R&D investment intensity and firm productivity and innovative output. Griliches studies this topic because of the slowdowns in the growth of productivity and R&D due to domestic inflation and decreased international competitiveness at the time. The author studies this topic by conducting a panel data regression analysis, in which control variables such as industry characteristics, firm size, and market structure are employed.

2.2.1 [Endogeneity Issues]

Griliches' (1987) paper, although a forefront study on the topic, is confronted with a major limitation which arises from the relationship explored: simultaneity bias. Do higher levels of R&D investment lead to increased firm productivity, or does increased productivity allow firms to spend more on R&D? Griliches mentions this issue in the text too. Baum et al. (2017) provide a method of accommodating the issue of endogeneity in this relationship by making use of the CDM model developed by Crépon et al. (1998). Baum et al. (2017) use a generalised Tobit model to handle the issue of selectivity bias, where only some firms innovate, and a two-stage estimation procedure to account for the simultaneity of equations. Another study by Abazi-Alili et al. (2016) addresses the issue of endogeneity by employing the same CDM model to control for the endogeneity of innovation. In this study, the authors describe the CDM model in a stylised way, explaining how the model is formalised in four equations: (i) the firm's decision to engage in innovation activities; (ii) the intensity with which the firm undertakes R&D; (iii) the innovation or knowledge production function; and (iv) the output production function, where knowledge is an input (Abazi-Alili et al., 2016). By addressing the limitations of the study and introducing the work of Baum et al. (2017) and Abazi-Alili et al. (2016) on the CDM model, I can gain further insights on the complex relationship between R&D investment intensity and firm performance for my own investigation. Through tackling the issue of endogeneity, the authors of both papers provide a more robust analysis of the relationship, and applying a similar way of thinking, I will better grasp the intricate interplay between the two variables in the context of high-tech industries like the semiconductor sector.

2.3 [The Relationship Between R&D Investment Intensity and Financial Performance]

The previous section of this chapter introduced the issue of endogeneity that arises in the relationship between R&D investment intensity and firm financial performance. In this section, I delve deeper into this relationship, explore related and relevant articles, and shed light on its dynamics, while also providing further clarification on endogeneity and any other issues that arise. The relationship between R&D investment intensity and financial performance has been the subject of extensive research in various contexts. In general, the conclusions drawn differ depending on what the unit of analysis is and depending on the setting in which the study was conducted. I will group and discuss studies based on the conclusions they arrive at in order to clearly outline the differing evidence provided by each paper and so that it is straightforward to navigate the sea of research that has been done on this topic.

Let me begin by looking at Zhu & Huang's (2012) study where they test the correlation between R&D investment intensity and the one-year lagged performance of Chinese listed IT firms. They use data from the 2007-2009 financial reports of Chinese listed IT firms that disclose their R&D expenditures and find that firms with an intensive investment strategy in R&D will have significantly larger financial performances recorded. A significant limitation of the paper is that it does not give any consideration to the aforementioned endogeneity issue, making it difficult to trust the conclusion of the paper. Paula & Silva Rocha (2021) find a direct and positive relationship between R&D intensity and financial performance. They sample 751 firms from six Latin American countries and use data from secondary sources in order to produce their results. However, their time horizon considered only spans five years, so their results may have been more comprehensive if the period was longer. In addition, this paper suffers the same major limitation as Zhu & Huang's (2012), where the issue of causality between the two variables is not addressed. A paper by Ayaydin & Karaaslan (2014) reaches the same conclusion as Zhu & Huang (2012) and Paula & Silva Rocha (2021), where they find that R&D intensity has a significant positive effect on firm performance. Ayaydin & Karaaslan (2014) employ a similar methodological approach to Baum et al. (2017) by looking at previous literature and building a model based on what other studies have done in the past. Their approach is slightly more technical and beyond the scope of this study, but it addresses the issue of endogeneity and finds a positive relationship between the variables. Ayaydin & Karaaslan (2014) give support to policymakers and business leaders that advocate pro R&D expenditure policies in high-tech sectors even in times of recession. This further underscores the significance and relevance of the relationship studied in this report. The US faces supply chain risks when it comes to assembly and testing of semiconductor chips. According to a report by Deloitte United States (2023) describing the semiconductor industry outlook for 2023, one of the main challenges US firms face is onshoring or nearshoring the assembly and testing of semiconductor chips, as most of the high-volume production facilities are offshore and outside the proximity of the US. If American chipmakers decide to revive manufacturing locations close to home, understanding how they can effectively allocate R&D investments will be crucial to their financial success.

Shin et al. (2017) find that the relationship between R&D ratio to net margin is negative for the whole sample of fabless and vertically integrated semiconductor firms from 2000-2010, suggesting that the industry may be overinvesting in R&D. The methodology follows an instrumental variables approach to deal with endogeneity which arises from the reverse causality of the relationship by taking the one-year lagged variables of R&D. Lagged values of the variable have been proven to meet the instrument exogeneity and relevance conditions in studies from Blundell et al. (1999) and Kleis et al. (2012). Shin et al. (2017) conceptualise firm performance in a similar way to my research: gross margin, return on assets (ROA), and Tobin's *q* are the three variables used to measure firm performance output. While this paper drops ROA in favour of EVA™, the other measures stay the same, meaning I will be able to compare my results to other studies that examined the same relationship. A final study that is relevant to my analysis is the one conducted by Hsu et al. (2013), where the authors arrive at an interesting conclusion. Using a sample of innovative and high-tech Taiwanese companies from 2000 to 2011, they conduct a regression analysis with a time-lagged effect of R&D expenditures and observe that firms with high levels of innovative energy (high R&D expenditures) have better stock returns and net sales, however, they also note lower operating income due to an increase in operating costs (Hsu et al., 2013). Again, the inclusion of the lagged variables of R&D expenditures solves the problem of simultaneity bias.

Having discussed previous literature, I can begin by identifying some current gaps in the knowledge. This will paint a clear picture of how this report is supposed to fit in alongside the work that has already been done, while restating its relevance and significance in the context of existing knowledge.

Previous studies offer contrasting conclusions on the relationship discussed. For example, some studies find a positive effect of R&D intensity on financial performance, while others a negative one. Inconsistent findings on the topic give me a reason to address these by examining the underlying factors that contribute to this variation. If I reach any contrasting results, I will have the opportunity to present these differences and provide arguments for why they exist. Additionally, the US is looking to regain its seat at the top of the table in the semiconductor world, as evidenced by the CHIPS and Science Act, introduced in the spring of 2020. From the time the Act was announced through the months following its enactment, companies in the semiconductor industry announced more than 40 new projects in the US totaling nearly 200 billion USD in private investments (Ravi, 2023). American policymakers are looking to reap the rewards of these investments and have a clear understanding how R&D expenditures affect the financial performance of US semiconductor firms, given the large number of studies with various findings. This paper tackles the issue directly and hopes to provide an answer to whether high R&D investment intensity is a viable and successful method of creating value. As a result, I present the first hypothesis, which is broken down into three sub-hypotheses:

H1: There is a positive and significant effect of R&D investment intensity on firm financial performance.

H1a: There is a positive and significant effect of R&D investment intensity on EVA ™.

H1b: There is a positive and significant effect of R&D investment intensity on gross profit margins.

H1c: There is a positive and significant effect of R&D investment intensity on Tobin's q.

All firms sampled in previous works on the topic are firms that have high levels of innovative output and invest heavily in R&D. Our sample of publicly listed US semiconductor firms fulfills this condition, evidenced by the fact that in 2021, US semiconductor companies invested one-fifth of their annual revenues, amounting to 50.2 billion USD, in R&D (Semiconductor Industry Association, 2022). The period I observe my findings on is a 10-year span, which is in line with choices made by authors in other previous literature and should be long enough to output robust results. Over the 10-year time period of interest, the world was hit by the COVID pandemic, specifically in 2020. It resulted in a supply-side recession during the first half of 2020 (Jomo & Chowdhury, 2020), which persisted for the rest of the year (Albanesi & Kim, 2021). During recessionary periods, it is reasonable to expect that investments will not be as fruitful as in good economic times, so determining whether this is the case in our context will provide additional understanding on whether semiconductor firms suffered losses during recessionary times.

H2: There is a negative and significant effect on firm financial performance during recessionary times.

This chapter has set the foundation for the empirical investigation and established the research objectives of this thesis. Reviewing previous studies has identified contrasting results and the issue of endogeneity arising from reverse causality as the main factors that require further investigation. To address these concerns, I propose using the one and two-period time lags of the natural logarithm of R&D investment intensity to estimate the relationship between R&D investment intensity and financial performance which will yield robust results.

CHAPTER 3 Data

This section presents the data source and sample, the variables of interest including controls, and provides some summary statistics on these variables.

3.1 [Data Source and Sample]

The dataset sample consists of publicly listed American semiconductor firms, extracted from Compustat through Wharton Research Data Services (WRDS). Compustat is a comprehensive database that includes data sourced from the financial statements of companies, providing financial ratios and fundamentals on publicly traded companies from North America. To narrow down the search to our specific list of firms, I filtered the results by the SIC code of semiconductor firms, 3674. The data covers the period 31st December 2012 – 31st December 2022. Given that they did not make a significant difference to the dataset and in order to ensure data consistency, 11 companies that had less than three observations of the R&D expense variable were removed from the list. This leaves us with a sample size of 151 publicly listed semiconductor firms that we have the required variables for. This sample size is in line with other studies that cover the same topic (Shin et al., 2017; Zhu & Huang, 2012; Ayaydin & Karaaslan, 2014).

3.2 [Variable Description]

All variables used in the analysis are provided by Compustat via WRDS, with the sole exception of the average cost of capital per year for the semiconductor industry, which is extracted from Damodaran (2022). I note that the panel dataset is unbalanced; certain variables do not have the full 1158 observations over the 10-year period, meaning that some companies only have data that spans for a smaller window than the one I wish to observe. However, the missingness of the data is likely to be random and unrelated to the variables of interest. This is because there are multiple reasons for which observations from financial statements during the period of interest are missing: a company could have been publicly listed during the period (i.e., in 2015, thus no data preceding this year would exist), a company could have been acquired or bought out during the period which would change its ownership structure from public to private, or simply that this database is a collection of information from various sources which can be subject to inconsistencies in reporting, mistakes during the collection process, or regulations which restrict data availability for certain firms. Therefore, I will proceed with the analysis, as STATA is capable of handling unbalanced panel datasets provided the data missing is random.

Our three dependent variables act as measures of financial performance. *EVA* measures the economic value added of a company, calculated following Grant's (2003) & Worthington & West's (2001) formula, which is expressed in Equation 1:

$$(1) \quad EVA = NOPAT - (Invested\ Capital * Cost\ of\ Capital)$$

NOPAT refers to the net operating profit after tax and is calculated by multiplying the operating income of a firm by its tax rate. The invested capital variable measures the funds contributed by shareholders and creditors to finance a company's operations. Finally, the cost of capital used is the average cost of capital for the semiconductor industry in the States each year, taken from Damodaran (2022). The number for *EVA* is reported in million USD, and it seems semiconductor firms do not perform too well in this metric as almost all observed variables are negative. These negative values stem from the fact that operating income is also negative for almost all firms, which then paints a clearer picture. According to (Goodman et al., 2019) the semiconductor industry cost structure is characterised by greater-than-normal fixed costs. The industry requires significant investments in facilities, equipment, and R&D, and as a result many firms may record revenues that do not cover these costs.

The second dependent variable is gross profit margin, or *GPM*. It is calculated by dividing gross profit by total revenue and is reported as a ratio. It measures a company's profit from its core business operations. Including *GPM* in the equation will allow me to measure to what extent, if any, R&D expenses significantly affect the profit from the core operations of semiconductor firms. 3 single observations out of 1158 for this variable are not recorded as either the gross profit or revenue were not reported in the period.

The final dependent variable is Tobin's *q*, or *TobinsQ*, which is calculated by dividing the total market capitalisation of the firm by its total assets and is thus expressed as a ratio. This is in line with work by Wang (2015), who state that the formula is the asset's market value divided by the asset's replacement cost. 245 single variables are missing for *TobinsQ*, but that still leaves plenty to maintain data integrity. Observing a *TobinsQ* variable greater than 1 is not uncommon in the data, and this may be partly explained by the fact that the market expects future growth in the industry, or that the assets of the firm are unique in such a way that their replacement cost is higher than their book value, leading to the market pricing them higher too.

Moving on to the independent variable of interest, R&D investment intensity (*RDInvInt*) is estimated through dividing a firm's R&D expense by its revenue during the period, outputting a ratio. The greater the value, the more R&D intense a firm is, meaning they invest a greater proportion of their revenues in R&D. 34 instances of *RDInvInt* are missing from the data since revenue numbers were not reported in that period. There are only 56 instances in the data where the value of R&D investment intensity is greater than 1, so it seems as if companies are able to manage their R&D expenses and keep them under control.

3.2.1 [Control Variables]

To eliminate sources of omitted variable bias, I will include several relevant and significant control variables which were chosen because of their inclusion in past literature on the topic. This selection of control variables creates a balance between parsimony and complexity; the model should fit new data well and be generalisable and not be too specific, otherwise it would overfit our dataset.

The first control variable included takes into account the firm's size. The *Size* variable is simply the natural logarithm of the total assets of the firm, and is the only control variable that is included in almost all previous studies (Ehie & Olibe, 2010; Shin et al., 2017; Ayaydin & Karaaslan, 2014; Baum et al., 2017; Hsu et al., 2013). Ehie & Olibe (2010) explain that firm size is measured as the natural logarithm of a firm's total sales to avoid any compounding effect of firm size on firm performance by controlling for economies and diseconomies of scale. Changing the variable to a logarithm means that the dependent variable will be interpreted as a relative percentage change, a crucial aspect of our results interpretation.

The remaining control variables are *Lev*, *Liq*, and *CapInt*, which measure the firm's leverage, liquidity, and capital intensity respectively. Leverage is included to control for any cross-sectional variations in firm value due to differences in capital structure (Pantzalis, 2001). It is computed by dividing the total debt of a firm by stockholders' equity. Firm liquidity is measured by the current ratio, computed as current assets divided by current liabilities, following approaches from Rahaman (2011) and Goddard et al. (2005). Liquidity indicates the speed at which a firm is able to react to sudden changes in its environment (Goddard et al., 2005), and controlling for this aspect will provide a level comparison across all firm in the sample. Lastly, capital intensity is measured as total assets divided by total revenue and is included since large semiconductor firms are very likely to have large sunk costs, so capital investment can influence performance (Shin et al., 2017).

3.3 [Descriptive Statistics]

This section presents descriptive statistics on the data, so that we get a clearer picture of the variables included in the analysis. The descriptive statistics are presented in Table 1. When observing the histograms of each variable, it was evident that there was skewness in the data, mostly created by significant outliers. Furthermore, the relationships between the variables were non-linear. In order to satisfy the assumption of linearity so that the model outputs consistent and unbiased coefficients, I performed a log transformation of the variables in the dataset that had strictly positive values, which included *TobinsQ*, *L1RDInvInt* (one period lag of *RDInvInt*), *L2RDInvInt* (two period lag of *RDInvInt*), *Liq*, and *CapInt*. The remaining three variables that had negative observations were transformed through a cubic root transformation, where the cube root of the value was taken and then multiplied by the sign of the initial value. Table 1 below presents the summary statistics, with *EVAcuberoot* being reported in USD millions, *GPMcuberoot*, ln*TobinsQ*, *L1lnRDInvInt*, *L2lnRDInvInt*, *Levcuberoot*, *lnLiq*, and *lnCapInt* being reported as a ratio, and *Size* as the natural logarithm of total assets.

The mean value of *EVAcuberoot* is -6.219 million USD, indicating that the average semiconductor firm in the sample is not generating enough return to cover its cost of capital. Therefore, EVA™ seems to be determined by the operations of the company itself, such as business strategies and cost management, rather than by any industry level factors such as market conditions. We observe a positive and healthy *GPMcuberoot* for firms in the sample with a mean value of 0.617, which is evidence that the core operations of the average firm in the sample are profitable. Most firms in the sample have healthy gross profit margins (before transformation) of 20-70% but a small sub-sample of firms with poor economic performances, especially during 2020 at the height of the Coronavirus pandemic, drag the mean of *GPM* down. *lnTobinsQ* has a mean value of 0.611, indicating that for the average publicly listed American semiconductor firm, the natural logarithm of the market value of assets is 0.611 times higher than their replacement cost. This is in line with expectations, as technological innovation is the way forward for semiconductor firms, and a Tobin's *q* value above 1 (before transformation) for firms in the sample reveals that the market expects these companies to be profitable in the future. As for *L1lnRDInvInt* & *L2lnRDInvInt*, the negative means of the variables tell us that on average firms spend a proportion lower than 1 of their total revenues on R&D expenditures from 2012-2022. This is in line with theory, as there are many costs that semiconductor firms must manage besides R&D expenditures. By looking at the median of the untransformed lagged variables we get a much more complete picture, which tells us that the median firm invests 16% of its sales in R&D, which is in line with findings from the Semiconductor Industry Association (2022).

As the mean natural logarithm of total assets is 6.43, the *Size* variable tells us that firm size is relatively large in the sample. Publicly listed semiconductor firms tend to report relatively large total asset values on their balance sheets because of the expensive equipment they employ in the production process. *Levcuberoot* shows us that firms in the industry have debt-to-equity ratios of around 20% before transformation. Due to high capital requirements and the cyclical nature of the industry, semiconductor companies may adopt conservative financing strategies in order to have strong balance sheets and be liquid. Thus, they may not lever themselves significantly, as observed. Furthermore, the mean value of *lnLiq*, the current ratio of the firm, is 0.994, and around 2.704 before transformation, which backs up the claim that semiconductor firms aim to manage to cover their short-term obligations. It is no surprise that the mean sample firm also has a mean *lnCapInt* value of 0.499, which indicates a capital intensity of above 1, as it is well-known that semiconductor firms incorporate many fixed assets such as machinery in the production of their goods.

Table 1: Summary Descriptive Statistics of the Panel Dataset

Variable	Mean	Std. Deviation	Min.	Max.	N	n
EVAcuberoot	-6.219	6.106	-26.474	26.688	1158	151
GPMcuberoot	0.617	0.624	-6.214	0.996	1155	151
lnTobinsQ	0.611	1.102	-2.732	5.327	913	125
L1lnRDInvInt	-1.945	1.386	-6.059	6.477	976	149
L2lnRDInvInt	-1.953	1.380	-6.059	6.477	827	148
Size (Ln)	6.43	2.61	-4.07	12.11	1158	151
Levcuberoot	0.598	0.722	-7.808	3.959	1158	151
lnLiq	.994	1.087	-6.768	4.567	1158	151
lnCapInt	.499	.720	-1.344	6.454	1124	151

Notes: This table presents the summary statistics of all variables from 2012-2022. The number of observations N & n varies due to availability of the data. All data has been extracted from Wharton Research Data Services (2023).

Table 2 displays the pairwise correlation coefficients between the variables of interest. The stars indicate significance at a 5% level. As can be seen in Table 2, the correlation between the main variables of interest, *L1lnRDInvInt* and *L2lnRDInvInt* and the dependent variables is significant for all cases. In the case of *EVAcuberoot* and *lnTobinsQ* the correlations are positive, and negative for *GPMcuberoot*. The positive correlations are in line with expectations from Hypotheses 1a and 1c. The magnitude of the correlation is highest for the one and two-period lags of R&D and Tobin's *q*, whereas the magnitude for the relationship between the lags and *EVAcuberoot* and *GPMcuberoot* is quite similar. This indicates that firms that have higher R&D intensity in the 2 years before the current period are firms that generate higher returns above their cost of capital, and firms whose market value of assets is also higher than their book value. However, firms that invest more heavily in R&D seem to be reporting lower gross profit margins than firms that invest less. This is in line with theory: if a larger proportion of revenue is spent, then profits will decrease. The *Size* variable correlations are significant for all variables. If the magnitude is positive, we can interpret it as larger firms have relatively higher values for the correlated variables, and if negative, larger firms have relatively lower values. Larger firms also seem to lever themselves to a larger extent, as shown by the positive 0.2658 correlation coefficient between the two variables. The liquidity coefficient is positive for all variables except for the correlation with Tobin's *q*, which shows that firms that have more current assets tend to exhibit lower Tobin *q* values. Lastly, capital intensity has no significant correlation with any variable except the *Size* variable, which indicates that larger firms are more capital intensive.

Table 2: Pairwise Correlation Coefficients

	EVAcr	*GPMcr*	*lnTQ*	*L1lnRD*	*L2lnRD*	*Size*	*Levcr*	*lnLiq*	*lnCapInt*
EVAcuberoot	1.0000								
GPMcuberoot	-0.0320	1.0000							
lnTobinsQ	0.2601*	-0.1564*	1.0000						
L1lnRDInvInt	0.2917*	-0.2785*	0.5206*	1.0000					
L2lnRDInvInt	0.2921*	-0.2447*	0.5105*	0.9563*	1.0000				
Size	-0.3586*	0.2910*	-0.3297*	-0.4268*	-0.4298*	1.0000			
Levcuberoot	-0.1029*	0.0890*	-0.1303*	-0.0787*	-0.0677	0.2658*	1.0000		
lnLiq	0.0775*	0.1056*	-0.1956*	0.1117*	0.1315*	0.2367*	0.0873*	1.0000	
lnCapInt	-0.0260	0.0025	-0.0098	0.0120	-0.0000	0.0917*	-0.0201	-0.0163	1.0000

Notes: This table presents the pairwise correlation coefficients of all variables from 2012-2022. All data has been extracted from Wharton Research Data Services (2023).

*Significance levels: * p<0.05*

Figure 1 in Appendix A presents the average R&D investment intensity of US semiconductor firms from 2012-2022. As we can observe in the figure, R&D intensity seems to have an upward trend during the period. This signifies that the importance of R&D intensity to these companies has been increasing during the period of interest. This is in line with what I presented in Chapter 2; as we are advancing and new technologies are developing, semiconductor firms are scrambling to make their chips more efficient and to improve supply chain management in order to remain competitive. There is one mean value in Figure 1 that stands out, and that is the one in 2014, where average R&D intensity in the sample recorded a value of 5. This means that in 2014, on average, publicly listed US semiconductor companies invested 5 times their revenues in R&D efforts. This value is abnormally high compared to the usual 0.25-0.8 range for R&D intensity. It may have been observed because of semiconductor firms' lower revenues during 2014.

CHAPTER 4 Methodology

This chapter discusses the methodological approach implemented in this paper. It will provide a step-by-step analysis of the procedure, beginning with data cleaning and ensuring its consistency, followed by outlining the econometric approach to computing the regression and what robustness checks were used to check the validity of the data.

In the initial stage of data processing, the dataset was thoroughly inspected to check for errors, obvious outliers, or measurement errors. Most variables include a few significant outlier values that deviate from the pattern of observations for the firm in question, however, as this is data taken directly from the financial statements of the companies, it is plausible to assume that they are not measured with error, but that they are actual observations. To verify this assumption, I cross-referenced the data extracted from Wharton Research Data Services (2023) for a smaller sample of firms within the dataset with data on the financial statements of the same firms from other online sources, and the values matched. Subsequently, I proceeded to remove all observations that had less than three observations of the R&D expense variable; this constituted of 11 firms only, which reduced the sample size to 151 firms. The data was then transported and analysed with the use of STATA, a statistical software package widely used in academic research.

To ensure adherence to key econometric assumptions, I started off by visually checking the scatter plots between each dependent variable and independent variable to confirm the assumption of linearity. All scatter plots demonstrated a linear pattern, satisfying the assumption of linearity. Fixed and random effects estimations are generally used to analyse panel datasets.

Fixed effects estimations isolate individual and time invariant unobservable characteristics that affect both the dependent and independent variable, and should be accounted for, otherwise the regression output would be biased due to omitted variable bias. After accounting for fixed effects, it is plausible to assume that there is no correlation between the error term and the independent variable, and thus we observe consistent and unbiased estimators of the coefficients. Random effects estimations account for the fact that the effect of a variable may differ across different firms in the sample, rather than assuming that there is one sole invariant characteristic that affects all firms in the sample. In general, fixed effects models are appropriate when the goal is to estimate the average effect of a variable within a group, while random effects models are more appropriate when the goal is to estimate the overall effect of a variable across multiple groups. (Axiomtutoring, 2023).

An overview of the equations estimated in Models 1 and 2 are shown below in Equations 2 and 3. Model 1 analyses the three dependent variables, *EVAcuberoot*, *GPMcuberoot*, and *lnTobinsQ*, and aims to understand the effect of the one period time lag of the natural logarithm of R&D investment intensity.

Model 2 does the same but with the two-period time lag of the independent variable of interest. Both models employ the use of the same control variables, as outlined in the equations below.

(2) $DepVar_{i,t} = \beta_0 + \beta_1 L1lnRDInvInt_{i,t} + \beta_2 Size_{i,t} + \beta_3 Levcuberoot_{i,t} + \beta_4 lnLiq_{i,t} + \beta_5 lnCapInt_{i,t} + i.DataYearFiscal_t + \epsilon_{i,t}$

(3) $DepVar_{i,t} = \beta_0 + \beta_1 L2lnRDInvInt_{i,t} + \beta_2 Size_{i,t} + \beta_3 Levcuberoot_{i,t} + \beta_4 lnLiq_{i,t} + \beta_5 lnCapInt_{i,t} + i.DataYearFiscal_t + \epsilon_{i,t}$

The Hausman test was used to decide between the fixed and random effects models for each regression. If the p-value exhibited by the test is above 0.05, then random and fixed effects estimations are efficient but random effects are more consistent. If the test outputs a significant result with a p-value below 0.05, random effects become inconsistent and fixed effects remain consistent. The results of each Hausman test can be viewed in Table 5 in Appendix A.

Another point of interest was the inclusion of year dummy variables as control variables, measured by the variable *DataYearFiscal,* in the regression which would shed some light on whether values were significantly higher or lower during certain years in the period observed, and to control for any significant differences, such as lower estimated values during recessionary years, which is the focus of Hypothesis 2. To evaluate whether these year effects were jointly significant or not, I performed a joint significant test to determine whether including years as dummy variables would significantly explain any variation in the outcome variables. If the resulting p-values of this test were significant at a 5% level, I included the *DataYearFiscal* variable as an additional control variable in the regression.

The homoskedasticty assumption of residuals was tested using a the Breusch and Pagan Lagrangian multiplier test for random effects and the Modified Wald test for groupwise heteroskedasticity for fixed effects. All output returned a significant result, indicating the presence of heteroskedasticity in residuals. Furthermore, I used a Skewness and Kurtosis tests for normality to verify the assumption that residuals are normally distributed. All output returned a significant result, indicating the presence of non-normality in residuals. However, this does not come as a surprise, since it is common knowledge that real-world financial data does not follow a normal distribution (Melnik, 2020). To control for this, I used robust standard errors after each regression equation estimation. Robust approaches are justified when extreme data points can be confidently regarded as outliers, which are removed or modified to limit data contamination (Pek et al., 2018). This is the case in my analysis, as all variables that exhibited outliers were modified.

By adhering to this methodological framework inspired by previous literature, this thesis outputs reliable results.

CHAPTER 5 Results & Discussion

Chapter 5 presents the results of the regression output and discusses the findings of the methodological approach employed, with a focus on the hypotheses and the meaning behind their acceptance or rejection. Tables 3 and 4 present the regression results of Models 1 and 2 respectively. The dependent variables are at the top, along with the estimation type, which is either fixed or random effects. For simplicity, the discussion of the results will present the coefficients post the back transformation of the cubic variables. This implies that the coefficients mentioned in text will differ from the regression output.

5.1 [Empirical Results]

Table 3 shows us that the effect of *L1lnRDInvInt* on *EVA* is significant at a 5% level, and outputs that on average, a one percent increase in *L1lnRDInvInt* leads to an approximate 0.0923 increase in *EVA* (in its original scale). Therefore, companies that raise their R&D investment intensity by 1% can expect to see a 92,300 USD increase in their EVA™. Although the effect is significant, semiconductor firms must invest heavily in R&D to increase their financial performance even slightly. The firm *Size* variable is the only other significant result in the regression from Model 1 Estimation 1 and reports a 5% significance level which showcases the fact that a one percent increase in the natural log of total assets of the firm decreases *EVA* by 0.324, or 324,000 USD. For the *EVA* calculation, invested capital multiplied by the cost of capital is subtracted from the net operating profit after tax. Invested capital is computed as total assets minus current liabilities, so it becomes clear that firms with larger total assets have a significantly lower economic value added.

Moving on to the second estimation of Model 1, we observe a significant effect at the 5% level of the one period time lag of *lnRDInvInt* on *GPM*, which tells us that a 1% increase in *L1lnRDInvInt* leads to a 0.003 decrease in the gross profit margin of a company. This is in line with theory, as spending a larger proportion of revenues on product development implies lower profits. The *Size* variable is significant at a 10% level and positive, indicating that a one percent increase in the natural log of total assets of the company increases *GPM* by approximately 0.00003. The small magnitude of this coefficient tells us that profitability in the industry does not arise from being a large company but rather from using assets effectively.

A random effects model allows for individual-specific effects that are assumed to be uncorrelated with the independent variables in the model. In other words, a random effects model assumes that differences between companies influence the dependent variable. The between R-squared values of 24.8% and 19.5% of the first two estimations suggest that differences between individual firms in the sample contribute to the variation in the dependent variable up to each respective magnitude.

The third estimation in Model 1 does not output any significant results for the variable of interest *L1lnRDInvInt*. However, we observe that in 2015 *lnTobinsQ* was significantly lower by 16.7% at a 5% level, in 2020 significantly higher by 42.1% at a 1% level, and 47.8% higher at a 1% level in 2021. This output is in comparison to the reference year of 2012. Further discussion and the meaning of these results will be provided in Chapter 5.3. This model accounts for fixed effects within each semiconductor firm which are characteristics unique to the firm that do not vary with time, a potential example being the location of its assembly line factories. The within R-squared value signifies that 14.4% of the within firm characteristics are accounted for by the variables in estimation 3 of Model 1.

Table 3: Model 1 Regression Results

Dependent Variable	(1) EVAcuberoot	(2) GPMcuberoot	(3) lnTobinsQ
Estimation Type	Random Effects	Random Effects	Fixed Effects
L1lnRDInvInt	0.452**	-0.140**	-0.0360
	(0.179)	(0.0622)	(0.0943)
Size	-0.687**	0.0320*	-0.0632
	(0.284)	(0.0166)	(0.0947)
Levcuberoot	-0.0984	0.0237	0.00327
	(0.161)	(0.0156)	(0.0451)
lnLiq	0.380	0.00565	0.0338
	(0.239)	(0.0444)	(0.0847)
lnCapInt	-0.0399	-0.0405	-0.0147
	(0.186)	(0.0295)	(0.0522)
Year Fixed Effects	No	No	Yes
Constant	-1.167	0.141	0.790
	(1.225)	(0.165)	(0.636)
Observations	949	948	758
R-squared (within)	0.001	0.027	0.144
R-squared (between)	0.248	0.195	0.016
Number of id	149	149	123

Notes: Robust standard errors are presented in parentheses. This table presents the results of Model 1, where the three dependent variables were regressed on the one period time lag of the natural logarithm of R&D investment intensity. The number of observations varies due to availability of the data. All data has been extracted from Wharton Research Data Services (2023) and includes data on a sample of 151 publicly listed American semiconductor firms.

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Table 4 presents the results of Model 2, which are almost identical to that of Model 1, although we see that some other coefficients become significant. In the first estimation of Model 2, I observe the same sign and significance of the lag of *lnRDInvInt* and the *Size* variables. If R&D expenditures two periods ago increase by 1%, semiconductor firms can expect to observe a 189,000 USD significant increase in their economic value added during the current period, almost double compared to the coefficient outputted in Model 1 estimation 1. The effect of *Size* is also similar but slightly greater, as a one percent increase in total assets will decrease economic value added by 395,400 USD. The variable measuring liquidity becomes significant, and a 1% increase in liquidity leads to a 207,500 USD increase in *EVA*, which tells us that firms that have more cash on hand also generate more EVA™. Three years are significant: 2016, 2020, and 2021. In 2016, *EVA* was 961,500 USD lower than in 2012, in 2020 and 2021 it was almost a million higher compared to 2012. The between R-squared value of 21.7% tells us that approximately one fifth of the variation between firms in *EVA* is accounted for by the variables in the model.

The second estimation outputs a negative and significant effect of *L2lnRDInvInt* on *GPM*, and if companies increase their R&D spending by 1% their gross profit margin is expected to decrease by 0.001 two years later. The effect of the *Size* variable is almost identical to the one form Model 1 estimation 2, which again supports the theory that firm size does not influence profits to a great extent. An R-squared of 15.8% is lower than the one observed in Model 1 with the one period time lag of *lnRDInvInt*, suggesting that semiconductor firms feel the payoff of their R&D expenditures sooner rather than later.

Finally, the third estimation of Model 2 yields insignificant results of *L2lnRDInvInt* on *lnTobinsQ*. The same three years, 2015, 2020, and 2021, provided significant results in the same direction as the Model 1 estimation, and with almost the same magnitude. This suggests that there may have been an event that affected the either the market's perception of semiconductor firms in these three years or the replacement cost of their assets.

Table 4: Model 2 Regression Results

Dependent Variable	(1) EVAcuberoot	(2) GPMcuberoot	(3) lnTobinsQ
Estimation Type	Random Effects	Random Effects	Fixed Effects
L2lnRDInvInt	0.574**	-0.100**	-0.0469
	(0.237)	(0.0457)	(0.0892)
Size	-0.734**	0.0326*	-0.0480
	(0.304)	(0.0178)	(0.105)
Levcuberoot	-0.195	0.0200	0.0278
	(0.183)	(0.0133)	(0.0432)
lnLiq	0.592**	-0.0435	0.113
	(0.261)	(0.0456)	(0.0989)
lnCapInt	0.0829	-0.0179*	-0.0371
	(0.186)	(0.0102)	(0.0499)
Year Fixed Effects	Yes	No	Yes
Constant	-0.906	0.259	0.561
	(1.258)	(0.166)	(0.722)
Observations	804	803	655
R-squared (within)	0.027	0.006	0.172
R-squared (between)	0.217	0.158	0.002
Number of id	148	148	122

Notes: Robust standard errors are presented in parentheses. This table presents the results of Model 2, where the three dependent variables were regressed on the two-period time lag of the natural logarithm of R&D investment intensity. The number of observations varies due to availability of the data. All data has been extracted from Wharton Research Data Services (2023) and includes data on a sample of 151 publicly listed American semiconductor firms.

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

5.2 [Conclusion on Hypotheses]

This sub-chapter concerns itself with either accepting or rejecting the hypotheses mentioned in Chapter 2.

With regards to Hypothesis 1a, there is insufficient evidence to reject it, and thus, we can accept its postulation that R&D investment intensity has a positive and significant effect on EVA™. The positive and significant results of the one and two period time lags of R&D expenditure provide evidence in favour of this. Therefore, investing heavily in R&D creates value for a semiconductor firm above its cost of capital, and as a result these companies can improve one metric of their financial performance by making such investments.

We reject Hypothesis 1b, which states that R&D investment intensity has a positive and significant effect on the gross profit margin of American semiconductor businesses. The significant negative effect of both lags of R&D expenditure tell us that firms must sacrifice part of their profits to go forward with investments in R&D.

Hypothesis 1c is also rejected, as previous lags of R&D expenditure do not have a significant effect on Tobin's *q* using the data in question. The insignificant coefficients imply that we cannot confidently say they are different from zero, indicating that R&D expenditures may not be a determinant of Tobin's *q* in our sample.

Lastly, Hypothesis 2 postulates that firm financial performance is negative during recessionary times, specifically 2020 up to and including 2022, during the time of the COVID pandemic. All dummy variables for the years 2020 and 2021 are significant and positive, indicating that EVA™ and Tobin's *q* were greater as compared to 2012 during these two years. The year 2022 has no significant results in either Model 1 or 2. Therefore, we reject Hypothesis 2, as firm financial performance as measured by the two variables seems to be positive during this period.

5.3 [Discussion]

Now that I have introduced the results and discussed their meaning for the hypotheses presented in this paper, it is time to compare them to what other studies on the topic have uncovered and consider their implications and what they mean in our context of publicly listed American semiconductor firms.

As mentioned previously, findings on this relationship vary widely, and depending on the sample of companies used, the context of the study, and the variables included in the analysis, the authors provide different results. My study finds a positive relationship between EVA™ and R&D intensity, a negative relationship between gross profit margin and R&D intensity, and no relationship between Tobin's *q* and the explanatory variable in question. These results are most similar to studies by Ayaydin & Karaaslan (2014) who find that R&D expenditures have a positive and significant effect on firm performance, Lin et al. (2006) who find an insignificant effect of R&D intensity on Tobin's *q*, and Zhu & Huang (2012) who again find a positive and significant effect of R&D intensity on operating income. My results are not in line with Shin et al. (2017), who find that R&D ratio has a small but positive significant effect on gross profit. Furthermore, Hsu et al. (2013) output that there is no significant effect of R&D intensity on operating income, whereas I find a significant negative effect on gross profit margin, a relatively similar metric of performance. Chen and Wu (2020) find that R&D investment intensity has a significantly positive effect on the ROA of companies, with human capital as a mediating variable. Lastly, Ehie & Olibe (2010) find a large positive and significant effect of R&D investment intensity on a firm's market value, which begs the question as to why my results show an insignificant effect on Tobin's *q*.

Not many studies focus on the effect of R&D intensity on economic value added, but the relationship sign and magnitude outputted are the ones I was expecting to observe, considering the fact that economic value added essentially measures value for shareholders, and there is no better way to do that than to have the most successful and best-selling product on the market at that time. Heavy R&D investments must be made in order to achieve such a feat, and the competitive nature of the US semiconductor market, alongside the country's willingness and ability to be a global leader in high-technology products pave the path for these fruitful investments to be made. The negative effect of R&D expenditure on gross profit margin is also in harmony with economic theory and previous studies discussed. The more money you spend on operations, product development, and anything else a company might need to spend money on, the less is available to put into your own pocket. Given the fact that they key to success for semiconductor firms is to keep their technological edge through R&D innovation, profits could be sacrificed at the expense of gaining market share, putting competitors out of business, or honoring government and civilian contracts that semiconductor firms are engaged in. Although being profitable is the number one goal for all companies, profits must be sacrificed from time to time while pursuing any of the aforementioned goals, and it seems in our 151 firm sample that this is the case. Finally, it seems that market perceptions of the semiconductor business and the replacement cost of machinery are not significantly influenced by R&D expenditure in our sample. A competitive advantage can be maintained if a firm could consistently have a high Q-ratio relative to its competitors over a long period (Lin et al., 2006). It seems that semiconductor firms do not get their competitive advantage solely from R&D expenditures. Other reasons for creating such an advantage may include being the first mover in a market, lobbying politicians, or having a greater market share.

The one interesting point of discussion is the fact that during 2020 and 2021, both the economic value and Q-ratio of firms was significantly higher than in 2012. Given the dire health consequences of the pandemic, the strengthening grip on world supply chains, and the overall organisational chaos that came along during those years, it is striking to see that semiconductor firms managed to remain financially healthy. There seems to be one prevailing reason for as to why this is: semiconductors are the key to technological advancement, and all governments and companies around the world understand that. Stakeholders in the industry simply cannot afford to stop designing new ways to make their products better. In a race for the world's most crucial technology, there is nothing that can come in the way of American firm behemoths and their success. Although the industry did go through a supply shortage nightmare during the pandemic (Kusum De, 2023) and was faced with diminishing demands from major buyers, it seems that the financial health of the companies was not impacted significantly during this period.

A final point that I feel should be touched upon and referenced once again is the dynamism in the semiconductor industry. In Chapter 1, I mention that if I find similar results to Chen and Wu (2020), there is evidence in favour of the fact that different factors rather than R&D investment intensity affect the financial performance of companies. They sample Taiwanese semiconductor firms and find that there is a significant effect of R&D investment intensity on the ROA of these firms. While my study does not directly replicate their results, the semiconductor sector's dynamic nature requires we consider variables beyond R&D investment alone. Market demand, technological advancements, competition, operational efficiency, and strategic decision-making all contribute to the financial outcomes of these firms. I can conclude that the constantly evolving nature of this industry provides evidence in favour that there are many factors that contribute to a company's financial success.

Having discussed how these findings fit into the scientific research on this topic and reasoned why we observe the output we do in Tables 3 and 4, it is time to move onto the conclusion of this paper.

CHAPTER 6 Conclusion

Chapter 6 of this paper concludes this report by re-stating the purpose of the study, summarising the research method and results, and makes inferences on what the results mean for real world applications and the scientific knowledge on the topic.

This thesis conducts a robust analysis of how R&D investment intensity affects semiconductor companies' financial performance. Previous research on this topic has yielded contrasting results, with some studies finding a positive effect, and others a negative one. Depending on the specific metrics of financial performance included, there may be no effect of R&D expenditures on these at all. Additionally, the research done here is aimed at providing a clear answer on the magnitude to which R&D expenditures influence the financial performance of semiconductor companies. There have been numerous studies on this topic, but the context of American semiconductor firms has not been the subject of discussion as often as it should, given the key role of the country in the global supply chain of the product. This was the purpose of my research, and it was directed towards answering the research question of this paper: How does R&D investment intensity affect the financial performance of companies?

In order to conduct the evaluation of this question, a sample of 151 American semiconductor firms over the years 2012-2022 was analysed using fixed and random-effects panel data regression techniques. The data for all variables used in the study is sourced from the financial statements of the companies themselves. My results indicate that if firms increase their R&D intensity, they can expect to generate a higher economic value added for the following two years. If firms have the aim of increasing their gross profit margins, then increasing R&D expenditures relative to revenues is not helpful, as it negatively impacts the profit margins of companies for the following two years. Lastly, my study did not provide any significant evidence that increasing R&D intensity leads to higher or lower Tobin q's values. The results of this study were subject to multiple checks to ensure their validity.

Moving on to implications for real world firms, stakeholders, and politicians, it is evident that R&D is a crucial component of the success of semiconductor companies. Chip manufacturing is becoming increasingly efficient and crucial to the success and development of future technologies. Every electronic appliance, from phones to dishwashers to rockets, run on semiconductors, and being the first in this market is of paramount significance to the development of our globalised planet. This study fits the pattern of contrasting results provided by academic literature on the topic, but this may simply be due to the fact that there are so many other factors in play that influence semiconductor firm performance. Moreover, technology is at its fastest pace of growth in decades, and with the addition of AI language models, semiconductor firms will be looking to implement these programs into their own supply chain network in order to become ever more efficient. With billions being poured into the survival of semiconductor firms by the American congress, the findings of this study also aim to help policymakers get a clearer picture of how to allocate these funds effectively.

With regards to future research, it would be beneficial for the industry and American government to evaluate the impact of the CHIPS and Science Act bill signed in 2022. The 50 billion USD in funds that were specifically allocated for R&D purposes will most definitely keep the US at the forefront of semiconductor engineering, and an in-depth research paper on this topic would provide some insightful information for shareholders and lawmakers.

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APPENDIX A

Table 5: Hausman Test for Fixed vs. Random Effects Regression

	χ^2 Statistic	Significance Level
Model 1, Estimate 1	19.10	0.1612
Model 1, Estimate 2	10.03	0.7598
Model 1, Estimate 3	47.46	0.0000*
Model 2, Estimate 1	11.46	0.5725
Model 2, Estimate 2	1.68	0.9999
Model 2, Estimate 3	35.49	0.0007*

Notes: Test of H0: Difference in coefficients not systematic. If the exhibited p-value is significant at a 5% level, fixed effects are consistent and efficient. If not, random effects are consistent and efficient.

*Significance levels: * p<0.05*

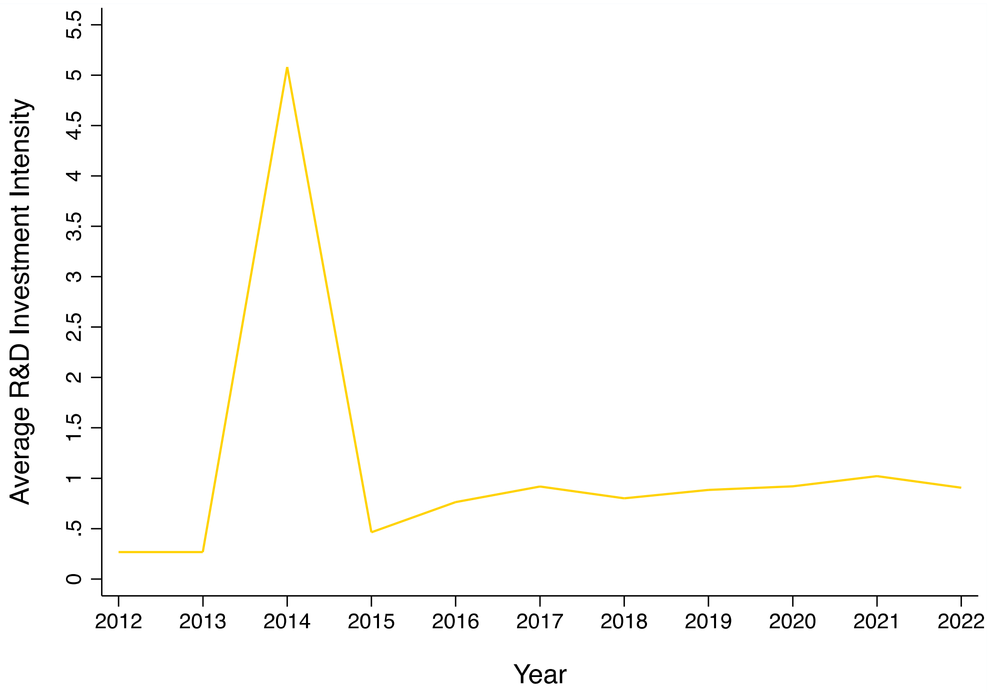

Figure 1: Average R&D Investment Intensity of US Semiconductor Firms from 2012-2022