Jan Erik Vie Nordeide
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The Effect of R&D Investments on Financial Performance:

An empirical study of companies listed on the Oslo Stock Exchange

Master's thesis in Economics and Business Administration: Finance & Investment
Supervisor: Christian Ewald
May 2023

Master's thesis

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Preface

Acknowledgement

We would like to express our gratitude to our supervisor, Dr. Christian Ewald, for his support, guidance and encouragement throughout this journey.

We would also like to extend our thanks to our families and friends, who have been a constant source of support and encouragement throughout the writing of this thesis. Their encouragement has been an important source of motivation, and we are forever grateful for their support.

Finally, we would like to dedicate this thesis to our friends and family, who have always encouraged and supported us in our academic pursuits. Their love and guidance has been instrumental in helping us reach this point, and we are deeply grateful for their presence in our lives.

Declaration

We, Jan Erik Vie Nordeide and Stian Juberg Varan, declare that this thesis entitled, “The Effect of R&D Investment on Financial Performance: An empirical study of companies listed on the Oslo Stock Exchange”, is our original work and has not been submitted for any degree or examination at any other academic institution. The content of this thesis is the sole responsibility of the authors.

We have followed ethical guidelines in conducting the research presented in this thesis and have not engaged in any plagiarism or academic misconduct. Any material and sources used in the preparation of this thesis have been properly cited and referenced in accordance with the accepted academic conventions.

Signed:
Jan Erik Vie Nordeide
JAN ERIK VIE NORDEIDE

Signed:
Stian J. Varan
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Abstract

In this master's thesis we examine the effect of investments in R&D on the financial performance of companies listed on the Oslo Stock Exchange. We study what performance could be expected by examining both the short-run and long-run effects. Our panel data is unbalanced, dynamic and has gaps between years. The dataset contains annual accounting data and the market value of companies at year-end. We find that R&D investments negatively affect short-term operating performance, measured through Return On Assets (ROA). We also find that R&D investments positively affect long-term market performance, measured through Tobin's Q. Our GMM estimates indicate that R&D investments take time to improve the financial performance of a given company.

Sammendrag

I denne masteroppgaven undersøker vi hvilken effekt investeringer i FoU har på den finansielle prestasjonen til selskaper notert på Oslo Børs. Vi studerer hvilken prestasjon som kan forventes ved å undersøke både kortsiktige og langsiktige effekter. Paneldataene våre er ubalanserte, dynamiske og har tomrom mellom noen år. Datasettet inneholder årlig regnskapsdata og markedsverdi ved årsskiftet. Vi finner at investeringer i FoU negativt påvirker kortsiktig operasjonell prestasjon, målt gjennom avkastning på eiendelene (ROA). Vi finner også at investeringer i FoU positivt påvirker langsiktig markedsprestasjon, målt gjennom Tobin's Q. Våre GMM-estimater indikerer at investeringer i FoU tar tid før de forbedrer den finansielle prestasjonen til et gitt selskap.

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1. Introduction

1.1 Background

Research & development (R&D) plays a critical role in driving innovation, progress, and growth (Sokolov-Mladenović et al., 2016). R&D investments are prevalent across institutions, organizations and companies around the world. For the latter, such investments can result in the creation of new and improved products and services, enhanced operational efficiency, and increased competitiveness (Blanco et al., 2016). However, the impact of R&D investments may not be immediately observable due to the inherent lag between the time of investment and its effect (Lev & Sougiannis, 1996).

According to Wendt et al. (2022), Norwegian companies invested approximately NOK 18.5 billion in R&D in 2010, which rose to NOK 38.3 billion in 2021. When considering all sectors and institutions, the total R&D expenditure amounted to NOK 42.7 billion and NOK 81.6 billion in 2010 and 2021, respectively. This increase aligns with the Norwegian government's long-term objective of achieving an R&D-to-GDP ratio of 3% (Meld. St. 3, 2018-2019). The government's emphasis on innovation has resulted in the development of grant and financing schemes that aim to give incentives and to support companies in their R&D investments. Studying the effect on financial performance generated from R&D expenditure is therefore of great interest.

We believe that the R&D investments made by the companies we study will make a substantial contribution towards a sustainable future. The development of innovative solutions through R&D can address societal and environmental challenges, enhance economic competitiveness and stimulate long-term growth.

1.2 Objective & Motivation

The objective of this thesis is to establish the importance of R&D by empirically demonstrating its relation to financial performance. The problem statement is as follows:

What is the effect of R&D investments on the financial performance of companies listed on the Oslo Stock Exchange?

To answer the problem statement, we formulate two research hypotheses, which are presented below. Although R&D investments take time to materialize, it is important to address the immediate consequences of R&D expenditure. Therefore, we analyze the problem statement with regards to both the short-term and long-term implications on financial performance. The hypotheses reflect the findings and argumentation in prior literature, and they also represent our expectations of the regression results. The research hypotheses are:

H_1: R&D investments have a negative short-term effect on financial performance.

H_2: R&D investments have a positive long-term effect on financial performance.

Despite the increased priority on R&D and supportive schemes, there is a limited amount of literature examining the actual effects of R&D investments for companies on the Oslo Stock Exchange. Because of this, stakeholders have a lack of research documenting how such investments affect company performance. Further analysis into this subject has implications for investors, companies, policymakers and academia.

The findings of this thesis show a negative short-term effect of R&D investments on operating performance, and a positive long-term effect on market performance. These results could impact investment strategies and decisions, leading to improved financial performance. Furthermore, they could potentially lead to changes in government policies and create a foundation for further research.

1.3 Research design & limitations

This research is limited to a time period between 2005 and 2021, and studies companies listed on the Oslo Stock Exchange with reported R&D expenditure. The sample is structured as panel data, and the method applied is two-step system GMM. We have utilized Return On Assets (ROA) as a metric to evaluate the operating performance, which is a representation of the short-term financial performance. For the long-term financial performance, Tobin's Q is used to assess the market performance. The models in this paper produce parameter estimates, and it is not the purpose of this thesis to provide estimates of causal relationships.

Survivorship bias is a potential risk that could affect our results as none of the companies in our sample went bankrupt, merged or were acquired during the time period we study. This could be attributed to the sample being relatively small, containing strong and robust companies that have endured for many years. Consequently, the inferences of the regression results may be biased.

Additionally, there is a risk of having selection bias in our data. According to Koh & Reeb (2015) some R&D expenditures may not be classified as R&D. Hence, there is a possibility that companies that actually have R&D expenditures are not included in our sample. Besides, R&D expenditure may also be under-reported in the financial statements.

2.0 Literature review

In this chapter, we provide an overview of the literature that forms the basis for this thesis.

Research on the relationship between R&D expenditure and financial performance for companies has been extensive in recent decades. However, the findings have been inconsistent, with some studies reporting a positive relationship and some a negative or no relationship at all. These inconsistencies could be attributed to differences in methodology and performance measures, in addition to differences in samples, objectives and time periods of the studies. Thus, the findings of a particular study cannot necessarily be generalized to other samples.

Literature on the returns of companies investing in R&D provides ongoing insights into how the market interprets and values such investments, as well as how these investments impact future returns and stock prices. Lev & Sougiannis (1996) identified a positive relationship between R&D expenditure and future stock returns in a study of U.S. companies between 1975 and 1991. Research conducted on UK companies by Anagnostopoulou & Levis (2006) supplemented this by showing that companies with higher R&D intensity generate persistent risk-adjusted stock returns several years into the future. Hou et al. (2022) conducted a cross-country analysis that emphasized the significance of R&D intensity. They concluded that companies with high R&D intensity are likely to experience higher stock returns in the future. These companies also reported higher future operating performance, in addition to higher return volatility and default probability. The studies above were not supported by Chan et al. (2001), who did not find evidence of a direct link between R&D expenditure and subsequent stock returns. They formed portfolios based on R&D intensity and found that stocks without R&D expenditure did not perform significantly worse than stocks with R&D. This research was conducted on a very specific sample within the technology industry, which could affect its generalizability.

Eberhart et al. (2004) studied companies that unexpectedly increased their R&D expenditure significantly, revealing positive abnormal returns for five years after the increase. They argue that this is because of a market under-reaction to the profits generated by the investments, which lead to a mispricing of the stock. Chambers et al. (2002) suggest risk compensation as an opposing reason for abnormal returns, where higher risk is offset by higher returns. Both the mispricing and risk compensation reasoning are supported by Lev & Sougiannis (1996). A third reason was put forward by Donelson & Resutek (2012), contending that improved performance is not solely due to R&D investments per se, but also stems from investors' expectations of the impact of such investments.

A market value approach is similar to using stock returns, but by incorporating the total value of a company's equity, it may provide a more comprehensive reflection of market performance. With a sample of 26 429 U.S. companies, Ehie & Olibe (2010) uncovered that R&D expenditure contributes to higher market value, after controlling for leverage, company size and industry. Sougiannis (1994) found that increasing R&D expenditure by one dollar led to an increase in market value by five dollars, on average, over the next seven years after the initial investment. Pantagakis et al. (2012) investigated market value for high-technology European companies and found a positive effect. They found that the optimal R&D intensity was at 41%, but it had a negative effect beyond that point. Supplementing this, Wang (2011) suggested that R&D expenditure must exceed a minimum level in order to lead to an increase in performance.

Studies focusing on ROA as a measure of financial performance provide conflicting results. Using a one-year and a two-year lagged version of ROA, Ullah et al. (2018) found that R&D expenditure had a positive effect on operating performance for companies in the UK between 2002 and 2016. The lagged variables were included in order to solve problems of endogeneity, which was the primary aim of their research. Alam et al. (2020) used data on several emerging economies and demonstrated a negative relation with regards to current year R&D intensity. However, when they used one-year lagged R&D intensity the relation with ROA was positive. This is corroborated in a study of Chinese IT companies, discovering that investing heavily in R&D strengthen their financial performance (Zhu & Huang, 2012). For Indian pharmaceutical companies, Jaisinghani (2016) showed a positive connection between current year ROA and R&D intensity. A possible non-linear relationship was also discovered, indicating diminishing returns. Contradicting this, Chen et al. (2019) found a negative link to current year R&D expenditure, which is explained by an increase in operating expenses in the short-term.

Vithessonthi & Racela (2016) reports R&D intensity to have a negative effect on ROA and positive effect on market performance. The authors argue that this is because of a lagged effect on operational performance, where investments today increase operating expenses that influence the concurrent returns negatively. The positive effect on market performance was measured through Tobin’s Q, which served as a proxy for the long-term financial performance. Connolly & Hirschey (2005) categorized their sample into three groups: manufacturing, non-manufacturing and one that included both. They further partitioned these categories into three groups based on the size of the companies. Their analysis showed that R&D expenditure was positively and significantly related to Tobin’s Q for all categories, except for small manufacturing companies. Lin et al. (2006) emphasized the significance of a commercial orientation when investing in R&D. They found that R&D expenditure alone had a negative but statistically insignificant effect. When considering commercial orientation as well, the effect was positive and significant. Szewczyk et al. (1996) studied market reactions to announcements of increased R&D expenditure, observing a positive effect on Tobin’s Q for high-technology companies and a negative effect for low-technology companies. Their findings provide evidence for the markets’ recognition of investment opportunities.

Ibhagui (2019) concludes that company size matters when analyzing R&D and financial performance. The impact of R&D on financial performance is stronger among smaller companies when it is negative, and stronger among larger companies when it is positive. Tsai & Wang (2005) found a “U-shaped” relationship between R&D productivity and company size. Their study revealed that both smaller and larger companies benefited more from R&D than medium-sized companies. They pointed out that smaller companies are able to rapidly respond to changing market needs, while larger companies gain an advantage from economies of scale.

Several studies have emphasized the need to include lagged versions of the R&D variable in order to investigate the impact of R&D expenditure on financial performance. According to Lee (2020), Chinese manufacturing companies experienced a positive effect when lagged R&D intensity was added for up to three years. In another study, by Lee & Choi (2015), five years of lagged R&D were used, but only the second and fifth lags were found to be significant. The effect was positive. Wintoki et al. (2012) suggested that using lagged variables for two years to capture the dynamic interrelatedness is sufficient. These findings, along with several of the aforementioned studies in this chapter, underscore the need to account for lagged R&D variables.

Morbey (1988) studied the effect of R&D on sales growth for companies in different industries within the U.S. The findings point out that companies with the highest long-term growth in sales invest heavily in R&D. Furthermore, this research indicates that an R&D intensity of at least 3% is necessary to provide long-term growth. The author advocates that when this 3% level of investment is not met, companies only support the current business, leaving future growth to chance.

Accounting treatment for R&D expenditures and its impact on value creation have been the subject of numerous studies. Shah et al. (2013) conducted research on UK companies that report under IFRS and found that capitalizing R&D expenditure is more relevant to value creation than immediately expensing them. In other words, there is a difference in how well accounting information can explain a company’s stock price depending on how R&D expenditures are accounted for. Lev & Sougiannis (1996) argued that capitalizing R&D expenses would provide reliable and economically relevant information, reinforcing the findings of Shah et al. (2013). This contradicts the reasoning behind the reporting standards of the U.S. GAAP, where R&D has to be immediately expensed. Thus, it is essential to be aware that the accounting treatment of R&D expenditure affect the comparability between different studies.

The sample, time period, performance measure and methodology all impact the relationships that are presented above. In addition to the accounting treatment of R&D expenditure, these factors contribute to the inconsistencies mentioned in the introduction to this chapter. This thesis has taken great care to address these factors, in order to ensure the application of appropriate statistical techniques that enhance the validity and robustness of the findings.

Table 2.1: Overview of prior literature.

Author(s)	Sample	Period	Performance measure	Methodology	Relationship**
Ullah et al. (2018)	101	2002 - 2016	ROA	OLS, Fixed Effects, Two-Step System GMM	Positive
Zhu & Huang (2012)	106*	2007 - 2009	ROA	Multiple regression (not specified)	Positive
Alam et al. (2020)	423	2006 - 2013	ROA	Two-Step System GMM	Positive
Chen et al. (2019)	96	2005 - 2016	ROA	Two-Step System GMM	Negative
Pantagakis et al. (2012)	39	2006 - 2010	ROA, MV	FGLS	Positive/Negative
Jaisinghani (2016)	55	2005 - 2014	ROA, ROS	Two-Step System GMM	Positive
Ibhagui (2019)	476	2002 - 2017	ROA, ROE, Tobin's Q	Threshold	Positive/Negative
Vithessonthi & Racela (2016)	1 899 - 20 195	1990 - 2013	ROA, ROS, Tobin's Q	OLS, 2SLS	Negative
Lin et al. (2006)	3 331*	1985 - 1999	Tobin's Q	SAS- MIXED Procedure	Positive
Connolly & Hirschey (2005)	15 709*	1997 - 2001	Tobin's Q	OLS	Positive
Lee & Choi (2015)	1 299	2001 - 2010	Tobin's Q	Fixed Effects	Positive
Szewczyk et al. (1996)	121	1979 - 1992	Tobin's Q, Returns	Cross-sectional	Positive
Lev & Sougianis (1996)	300	1971 - 1987	Returns	Instrumental Variables, Almon lags, Pooled OLS	Positive
Eberhart et al. (2004)	3 148	1951 - 2001	Returns	Fama & French-, Carhart factor models	Positive
Chambers et al. (2002)	72 317*	1984 - 1998	Returns	Fama & French 3-factor model	Positive
Donelson & Resutek (2012)	1 600	1973 - 2008	Returns	Fama & MacBeth	Positive
Hou et al. (2021)	418 067*	1981 - 2018	Returns	Fama & MacBeth, OLS, WLS	Positive
Anagnostopolou & Levis (2008)	770	1990 - 2003	Returns	Cross-sectional	Positive
Chan et al. (2001)	238 - 1 888	1975 - 1995	Returns	Cross-sectional, Fama & French-, Carhart factor models	None
Sougiannis (1994)	573	1975 - 1985	Earnings	Cross-sectional, Almon lags	Positive
Lee (2020)	34	2007 - 2017	MV	Fixed Effects (PLS), Random Effects (Pooled EGLS)	Positive
Shah et al. (2013)	8 227*	2001 - 2011	MV	Fixed Effects	Positive/Negative
Ehie & Olibe (2010)	26 429	1990 - 2007	MV	OLS	Positive
Wang (2011)	40	2001 - 2008	ROE	First-order-, Quadratic-, Cubic model	Positive
Morbey (1988)	598 - 859	1976 - 1985	SG, PM	Not specified	Positive/Negative
Tsai & Wang (2005)	126	1994 - 2000	TFP	Fixed Effects	Non-linear

**Company-year observations. The specific number of companies in the sample is not reported.*

***These are the primary relationships a given study present. There might however be more relationships, depending on performance measures, research purpose, etc. The relationships are not depicted in order according to the performance measure(s) in the table.*

MV = Market Value. ROS = Return On Sales. ROE = Return On Equity. SG = Sales Growth. PM = Performance Measure (see the study). TFP = Total Factor Productivity.

3.0 Data

This chapter describes the dataset and the processing of our data, it presents the definition of our variables, the descriptive statistics and the correlation matrix.

3.1 The dataset

Our dataset is structured as a dynamic panel, where each company constitutes its own group in the panel, that is observed over time. The panel is unbalanced as some companies have more observations than others, and there are gaps between years due to missing values. Since we expect a delayed effect of R&D investments on financial performance, the dataset contains lagged versions of *ROA*, *Tobin's Q* and *R&D Intensity.*

The data was extracted from the Compustat Global database and consists of annual accounting data as well as the year-end market value of 51 companies listed on the Oslo Stock Exchange. The dataset contains observations from 2005 to 2021, corresponding with the implementation of IFRS (2005) and the last available annual data (2021) at the time of writing. We utilized Stata for the processing stage, the statistical tests and for running our regressions.

Companies listed on the Oslo Stock Exchange are all subject to the IFRS, the IAS and the associated regulations (Regnskapsloven Art 4., 2023). The accounting principles, rules and practices that follow are thereby determinants of how R&D expenditure is reported; either immediately expensed or capitalized and listed on the balance sheet. R&D expenditure represent a given company's total expenditure on R&D. When extracted from Compustat, both the immediately expensed and the costs associated with the capitalized investments are included in the variable.

To ensure the analytical suitability of the dataset, specific criteria for each company and observation was established. The first requirement was that every company included in the dataset had to report R&D expenditure for a minimum of five years, but not necessarily consecutively. This was essential to ensure that each company had an adequate number of observations for the analysis. Secondly, we had to address the presence of outliers and missing values, which could potentially distort our results. Distribution plots and tabulations for each variable were employed to identify values that should be classified as outliers. Applying natural logarithmic transformations helped to reduce the number of potential outliers that required removal. Observations with missing values for key variables were also dropped. After addressing these issues, we assured the quality of the dataset by going through the descriptive statistics, which are presented later in *Table 3.3*.

After imposing our initial requirement regarding R&D expenditure, our original dataset comprised 740 observations. Following the process of addressing any outliers and missing values, our final dataset ended up with 577 observations, representing 51 different companies. In *Table 3.1*, we illustrate how these companies are distributed across the various industries represented in our dataset.

Table 3.1: Industries.

Industry	No. of companies
Consumer discretionary*	3
Consumer staples**	5
Energy	11
Finance	1
Health & Medicine	5
Industrial	8
Materials	4
Real estate	0
Technology	12
Telecommunication	2
Utilities	0
Total	51

*Consumer discretionary consists of companies that sell non-essential products and services.

**Consumer staples consists of companies that sell essential products and services.

The industries are partitioned according to Euronext (2023). Of all the industries, only *Real estate* and *Utilities* are not represented. Even though some industries are more represented than others, our dataset broadly represent the exchange. The presence of a higher number of companies in *Technology*, *Industrial* and *Energy* is not surprising, as they are major industries on the exchange. However, a more uniform distribution would have been desirable.

3.2 Variables

Dependent variables

ROA and *Tobin's Q* are the dependent variables in our respective models. *ROA* captures the short-term operating performance of companies and allows us to measure how effectively a given company produce profits relative to its assets (Vithessonthi & Racela, 2016). A one-year and a two-year version of *ROA* as independent variables are included to analyze the effect over time. It also allows us to solve some methodological issues regarding endogeneity, which we will come back to in the next chapter.

ROA is calculated as:

$$ROA = \frac{Net\ Income}{Total\ Assets}$$

Tobin's Q is a measurement that reflects the expectations regarding future financial prospects of companies. With similar reasoning as for *ROA*, we have included both one-year and two-year lagged version of this variable. *Tobin's Q* can be calculated in several ways, but it generally expresses the market value of equity divided by the replacement cost of the company's assets. Because of difficulties in obtaining the replacement cost, we followed the procedures of Gompers et al. (2003) and Kaplan & Zingales (1997):

$$Tobin's\ Q = \frac{Total\ Assets + Market\ Value\ of\ Equity - Book\ Value\ of\ Equity}{Total\ Assets}$$

Measuring R&D

A key variable in our analysis is *R&D Intensity*, which represents the level of R&D expenditure of a given company. This measurement is relative to a company's revenue, which allows for comparison between companies and prior literature. *R&D Intensity* gives an indication of the commitment towards R&D investments, which would not be apparent when using absolute figures. The calculation is as follows:

$$R\&D\ Intensity = \frac{R\&D\ Expenditure}{Revenue}$$

Control variables

We include debt-to-equity ratio (Deratio) as a variable to control for the inherent risk of debt financing and the associated obligations. Additionally, debt could allow companies to invest more into R&D, which may influence financial performance. This is computed as:

$$Deratio = \frac{Total\ Debt}{Total\ Equity}$$

Company size (Size) is an important control variable because it reflects economies of scale and advantages related to market dominance. The natural logarithm of a company's revenue is used as a proxy for size:

$$Size = \ln(Revenue)$$

Year-dummies (Year) is used to control for macroeconomic changes, shocks to the economy and other time-varying effects.

Industry-dummies (Industry) helps to mitigate potential bias that can arise from unobserved industry-specific factors that can affect financial performance. For example, the *Technology* industry is likely to be more dependent on R&D than *Consumer Staples*.

The variables are summed up in the following table:

Table 3.2: Variable definitions.

Variable	Definition of variable	Compustat code
Total Assets	Total value of all items reported as assets in the balance sheet.	AT
Company name	Company name.	CONM
Currency	The currency of which the company's financial data is reported.	CURCD
Total Debt	Total value of all items reported as liabilities in the balance sheet.	LT
Net income*	Net income based on a company's consolidated statements.	NICON
Price	Close price of the day for a security, year-end.	PRCCD
R&D Expenditure	Total expenditure on R&D, including capitalized R&D and related costs.	XRD
Revenue	Gross income received from all divisions of a company.	REVT
Shares	Number of common/ordinary shares outstanding at year-end.	CSHOC
Total Equity	Total value of a company's equity.	(AT - LT)
Market Value	Market value at year-end.	(PRCCD * CSHOC)
ROA	The return on assets.	
L1ROA	1-year lagged version of ROA.	
L2ROA	2-year lagged version of ROA.	
Tobin's Q**	Tobin's Q, express the ratio between market value and replacement cost of assets.	
L1TOBQ	1-year lagged version of Tobin's Q.	
L2TOBQ	2-year lagged version of Tobin's Q.	
R&D Intensity	Proxy for a company's R&D investment intensity.	
L1RDINT	1-year lagged version of R&D Intensity.	
L2RDINT	2-year lagged version of R&D Intensity.	
Size	Proxy for a company's size.	
Deratio	Debt-to-equity ratio.	
Year	Dummy-variables for a given year.	
Industry	Dummy-variables for a given industry.	

**Compustat Global did not have any data of non-consolidated net income.*

***The calculation is based on Gompers et al. (2003) and Kaplan & Zingales (1997).*

Data from the Compustat Global database is standardized.

3.3 Descriptive statistics & the correlation matrix

Table 3.3: Descriptive statistics.

Variable		Mean	Median	Std. dev.	Min	Max		Observations
ROA	overall	-.0154046	.02998	.2153575	-1.714705	.3441885		N = 577
	between			.1780986	-.7772286	.1788501		n = 51
	within			.1508675	-1.364813	.6940808	T	bar = 11.3137
L1ROA	overall	-.0154176	.02139	.2018372	-1.714705	.3441885		N = 577
	between			.1547508	-.7308226	.1615172		n = 51
	within			.146347	-1.364315	.715405	T	bar = 11.3137
L2ROA	overall	-.0144463	.01386	.1953828	-1.714705	.3441885		N = 577
	between			.140935	-.6340433	.1481407		n = 51
	within			.1479787	-1.382346	.6765472	T	bar = 11.3137
Tobin's Q	overall	2.336686	1.60351	2.190102	.5973814	16.95292		N = 577
	between			1.509228	.7787888	6.569701		n = 51
	within			1.583411	-2.727948	13.50833	T	bar = 11.3137
L1TOBQ	overall	2.036242	1.48662	1.971447	0	16.34425		N = 577
	between			1.22867	.6851228	5.257408		n = 51
	within			1.54086	-3.221165	13.12308	T	bar = 11.3137
L2TOBQ	overall	1.745333	1.34345	1.729102	0	11.97404		N = 577
	between			.9895438	.5962149	4.319826		n = 51
	within			1.417624	-2.574492	10.12612	T	bar = 11.3137
R&D Intensity	overall	.1486316	.01937	.9137743	.0000387	16.46935		N = 577
	between			.6452432	.0014153	3.722053		n = 51
	within			.7624681	-3.502786	12.89593	T	bar = 11.3137
L1INT	overall	.143058	.01465	.9141035	0	16.46935		N = 577
	between			.6404246	.0008004	3.705611		n = 51
	within			.7657437	-3.562553	12.9068	T	bar = 11.3137
L2INT	overall	.1365353	.00946	.9142229	0	16.46935		N = 577
	between			.6323288	.0006262	3.687961		n = 51
	within			.7706724	-3.551425	12.91792	T	bar = 11.3137
Deratio	overall	1.640352	1.07224	3.134154	.0445604	51.66637		N = 577
	between			1.535678	.1116543	7.159651		n = 51
	within			2.78104	-4.985653	46.14707	T	bar = 11.3137
Size	overall	7.969625	8.07746	2.497745	.0889262	13.65782		N = 577
	between			2.382718	3.694545	13.19043		n = 51
	within			.6640559	3.62999	10.54812	T	bar = 11.3137

Descriptive statistics for "between" and "within" refer to statistics between the groups of the panel and within the groups, respectively. These statistics are not considered essential to discuss or elaborate further on, but for the sake of transparency, we have included them in this table. The lagged variables are not of focus either, because only the current editions are important in this context. They are however included for the same reason as for "between" and "within".

The mean of *ROA* is -0.0154, suggesting that the companies on average experience negative profitability, and are unable to generate positive returns from their assets. For *Tobin's Q*, a higher value than 1 means that the market value of the company is larger than the replacement cost of the company’s assets. A mean of 2.3366 therefore means that the market value is 2.3366 times larger than the replacement cost of its assets.

R&D Intensity has a mean of 0.1486, equivalent to spending 14.86% of their revenues on R&D on average. Previous literature shows a large variation in R&D Intensity, where some have a smaller level of intensity compared to our dataset, while others have a similar level (Ullah et al., 2018; Jaisinghani, 2016; Eberhart et al., 2004; Ehie & Olibe, 2010).

Deratio has a mean of 1.6403, that is to say companies are financed with more debt than equity. Some companies are heavily leveraged, as can be seen from the maximum value of *Derati*o exceeding 51.

Skewness depicts the asymmetry of a probability distribution. By comparing the means to the medians, it is observed that all the variables are positively skewed, except from *ROA* and *Size*, which have negative skewness. This is apparent as *ROA* and *Size* have a median that is higher than the mean. *R&D Intensity* is the variable with the highest positive skewness, and *ROA* is the variable with the lowest negative. The skewness of *R&D Intensity* indicates that there are some companies with a higher intensity than the majority of companies. These companies belong in R&D intensive industries, which emphasizes the importance of controlling for industry in the models. The skewness of *ROA* suggests that a few companies perform worse than the majority. Because we dealt with outliers in the pre-processing stage, the right-tailed and left-tailed probability distributions of our variables are not worrisome.

Table 3.4: Correlation matrix.

	ROA	L1ROA	L2ROA	Tobin's Q	L1TOBQ	L2TOBQ	R&D Intensity	L1INT	L2INT	Size	Deratio
ROA	1.0000										
L1ROA	0.5220	1.0000									
L2ROA	0.3756	0.5366	1.0000								
Tobin's Q	-0.0026	-0.0148	-0.0803	1.0000							
L1TOBQ	-0.0141	-0.0649	-0.0768	0.7090	1.0000						
L2TOBQ	-0.0404	-0.0806	-0.1493	0.4692	0.6607	1.0000					
R&D Intensity	-0.2564	-0.1354	-0.0647	0.1219	0.0343	-0.0109	1.0000				
L1INT	-0.2710	-0.2710	-0.1388	0.1649	0.1495	0.0533	0.3708	1.0000			
L2INT	-0.2092	-0.2867	-0.2767	0.1421	0.1944	0.1834	0.0446	0.3713	1.0000		
Size	0.3676	0.3247	0.3170	-0.4136	-0.3315	-0.2505	-0.3065	-0.2388	-0.1533	1.0000	
Deratio	-0.0971	-0.1464	-0.1370	-0.0886	-0.1031	-0.1035	-0.0559	-0.0522	-0.0534	0.0512	1.0000

The correlation coefficients between *ROA* and its first lag, *L1ROA* as well as between *Tobin's Q* and its first lag, *L1TOBQ*, are 0.5220 and 0.5366, respectively. The corresponding correlation coefficient between L1ROA and its second lag, *L2ROA* is 0.5366. For *L1TOBQ* and its second lag, *L2TOBQ*, the correlation coefficient is 0.6607. These relatively strong positive correlations indicate that it is important to include lagged versions of the dependent variables in the models.

4.0 Methodology and Models

Due to the dynamic relationship of our variables and our expectation of endogeneity problems, we apply the Generalized Method of Moments (GMM). This chapter explains why endogeneity problems are a concern for our purpose and how it may lead to inconsistent estimates. Subsequently, we elaborate on how we used OLS and Fixed Effects to reveal endogeneity and its associated problems. Then, we expand on the GMM in detail and how it addresses endogeneity. We conclude the chapter by presenting our models and providing details on our regression syntax.

4.1 Endogeneity

Endogeneity is a condition where the independent variables of a model are correlated with the error term of the model, or when there is a correlation among the error terms themselves (Roberts & Whited, 2013). If not addressed properly, endogeneity can give inconsistent estimates, wrong signs for the coefficients, incorrect inferences, inappropriate theoretical interpretations and misleading conclusions (Ullah et al., 2018).

To illustrate, consider the following general model:

$$y = \alpha + \beta 1 * x1_{it} + \beta 2 * x2_{it} + \cdots + \beta n * xn_{it} + u \ (1)$$

An independent variable, *x*, is endogenous if it is correlated with the error term, *u*.

There are several sources to endogeneity, and for our models we expect these sources to be simultaneity, dynamic endogeneity and unobserved heterogeneity (Roberts & Whited, 2013; Wintoki et al., 2012). While omitted variable bias is a potential contributor to endogeneity, it is not a primary source of concern. This bias is related to unobserved heterogeneity, but is unlikely to create issues for our models (Ullah et al., 2018).

Simultaneity is a condition where at least one of the independent variables in a model is determined simultaneously with the dependent variable of the model (Wooldridge, 2002). In our case, the financial performance of a company could affect R&D expenditure, while R&D expenditure could also affect the financial performance of the company. This means that R&D expenditure as an explanatory variable would be correlated with the error term, *u*, in equation (1). This correlation can create endogeneity problems in our model and affect the reliability of our estimates.

Dynamic endogeneity is a version of simultaneity that arise when values of the dependent variable across time influence the current value of an independent variable (Li et al., 2021). In this study, past realizations of company performance can influence current R&D expenditure. For instance, a company's management could decide to allocate more resources to R&D because of strong financial performance in the past.

Unobserved heterogeneity refers to differences in individual characteristics or factors that vary across companies. These differences are not easily measured, but could still be present in the data. Unobserved characteristics or factors are typically associated with company fixed effects. When analyzing a company's financial performance and R&D expenditure, these could cause unobserved heterogeneity (Gormley & Matsa, 2013). To illustrate this, we can add the unobserved heterogeneity, expressed as *q*, to equation (1), where *q* represents unobservable factors (Wooldridge, 2002):

$$y = \alpha + \beta 1 * x1_{it} + \beta 2 * x2_{it} + \cdots + \beta n * xn_{it} + q + u \ (2)$$

Unobservable heterogeneity could be present in our model if the financial performance created by R&D in part is a result of management, strategy, culture or other similar company-specific characteristics and factors.

4.2 OLS & Fixed Effects

OLS is a common linear regression approach to estimate parameters. With OLS, the sum of the squared distances between the observed values and the values predicted by the model are minimized (Hammervold, 2020). This approach depends on assumptions of linearity, independence, homoscedasticity, normality and no multicollinearity (Kutner et al., 2005). For the independence assumption to be fulfilled, the independent variables have to be uncorrelated with the error term. Presence of endogeneity is a clear violation of this assumption (Abdallah et al., 2015).

According to Semadeni et al. (2014), even low levels of endogeneity can affect OLS estimates significantly. Firstly, endogeneity can result in overestimated coefficients that become pronounced as the level of endogeneity increases. Secondly, the standard errors decrease as the level of endogeneity rises. Thirdly, the OLS estimates are more likely to provide significant results, indicating interrelations between the model regressors that may not be true. However, if the regressors were exogenous and if there was no heteroscedasticity, OLS could be an efficient GMM estimator (Baum et al. 2003).

To determine if OLS is an appropriate approach and to detect indications of endogeneity, we ran tests for autocorrelation and heteroscedasticity. The results revealed the presence of both, which means that OLS is not a suitable approach.

A Fixed Effects regression is used to estimate parameters while also controlling for unobserved company-specific effects. This is done by subtracting the mean of each company’s observations from the observed values. With a Random Effects approach, a model assumes that these company-specific effects are uncorrelated with the independent variables (Wooldridge, 2002).

A Hausman test determines if the estimates produced from a Fixed Effects- and a Random Effects regression are significantly different. If they are, the company-specific effects are correlated with the explanatory variables, and a Fixed Effects model is preferred. In this case, the Hausman test has revealed unobserved heterogeneity that the Random Effects model is not able to address. The Fixed Effects model is able to address unobserved heterogeneity given that these company-specific effects are constant over time. However, because of simultaneity and dynamic endogeneity, these effects are likely to not be constant over time in our sample. This is because the within-unit variation may not capture the time-varying factors, resulting in correlation between the independent variables and the error term.

Consequently, the strict assumption of exogeneity is violated, and the Fixed Effects model is no longer suitable (Hammervold, 2020).

Table 5.1 and Table 5.2 present the OLS and Fixed Effects regression results for *ROA* and *Tobin's Q*, respectively.

4.3 Generalized Method of Moments (GMM)

The Generalized Method of Moments (GMM) is a statistical model that provide parameter estimates, address problems of endogeneity while also capturing the dynamic relations between variables. GMM deals with unobserved heterogeneity, simultaneity and dynamic endogeneity through the creation of instruments. These instruments estimate the company fixed effects, and they are created from variables assumed to be endogenous as well as the lagged dependent variables. An elaboration of instruments will be provided in section *4.3.1 Instruments.*

GMM was initially introduced by Hansen (1982), and was then further developed by Arellano & Bond (1991) and Blundell & Bond (1998). The method is commonly used on dynamic panel data where the causal relations are dynamic over time. For example, the financial performance of a company in a given year may be caused by the R&D expenditure not only in that year, but also in previous years. Additionally, current year R&D expenditure may cause the company's future financial performance.

GMM works well in situations where past realizations of the dependent variable influence itself (Børing & Mark, 2022). For example, *ROA* from previous years could influence current year *ROA*. In practice, GMM allows us to include lagged values of the dependent variable on the right-hand-side of the model equation. If there are interrelations between the lagged version of the dependent variable and another independent variable, the estimates from a Fixed Effects regression may be biased (Wooldridge, 2002), as we elaborated on in the previous section.

The strict exogeneity assumption is relaxed with the GMM, because of the creation of instruments. Furthermore, because company fixed effects are accounted for in a GMM model, the problem of unobserved heterogeneity is addressed (Wintoki et al., 2012).

There are two main approaches to a GMM regression, namely system GMM and difference GMM. The former corrects for endogeneity by introducing more instruments than the latter, which increases the efficiency of the model. System GMM also transforms the instruments to become uncorrelated with the fixed effects (Blundell & Bond, 1998). When dealing with an unbalanced dataset, system GMM reduces data loss compared to difference GMM, which widens the gap of missing values. This is achieved by using forward orthogonal deviations, which means that system GMM subtracts the average of all available future observations from the current observation. With difference GMM, the previous observation is subtracted from the current observation (Roodman, 2009). Because our dataset is unbalanced, we apply system GMM.

The system GMM approach has two possible specifications: one-step or two-step. The two-step specification is preferred to one-step, because it is more robust to heteroscedasticity and autocorrelation. Furthermore, the two-step system GMM tends to be more efficient than one-step system GMM when the number of moment conditions are large, which often is the case (Roodman, 2009). Moment conditions are sets of equations that define the moments of the data and are used to estimate the model parameters, meaning that they describe the relationship between the variables. These equations are used to construct a criterion function, which is then optimized to obtain the parameter estimates. Both Arellano & Bond (1991) and Blundell & Bond (1995) identified that the two-step GMM estimator has better small sample properties than one-step system GMM, particularly when the number of time periods is relatively large.

It is important to be aware of the limitations of GMM when applying it for data analysis. GMM is a complicated method that may produce invalid estimates if executed incorrectly (Roodman, 2009). A potential concern when applying GMM is the problem of the model becoming a “black box”, where data is processed, and the model produces an output of which the specific calculations are unobservable.

4.3.1 Instruments

Instruments address problems of endogeneity in statistical analysis. They are created by identifying external sources of variation that are correlated with variables assumed to be endogenous, but not affected by other endogenous sources. These instruments are then used in a model to produce more reliable and consistent estimates, even when the model includes endogenous variables. The use of instrumental variables increases efficiency and reduces bias caused by endogeneity (Baum et al., 2003; Stock et al., 2002). When using instruments, there are two assumptions that must be fulfilled: relevance and exogeneity.

The relevance assumption demands that the instruments, Z, are strongly correlated with the endogenous variables, X, in a given model (Stock et al., 2002). Identifying weak instruments is important because the inclusion of them may provide unreliable estimates. The solution is to get better instruments or to discard the weak instruments (Baum et al., 2003).

For illustration, the relevance assumption can be expressed as the following:

$$corr(Z, X) \neq 0$$

The exogeneity assumption requires the regressors to be exogenous (Stock et al., 2002). This can be expressed as such:

$$corr(Z, u) = 0$$

This means that the instrument, Z, affects the dependent variable, y, through its influence on the endogenous variable, X, (Roberts & Whited, 2013). Because the error term, u, is unobservable, this assumption cannot be tested. Nevertheless, this assumption does not have to be tested directly. This is because it is possible to test whether the model is correctly specified or not, and if the instruments are valid through the Hansen test.

4.3.2 Hansen test

A general guideline when using GMM is that the number of instruments should not exceed the number of groups in the panel (Roodman, 2009). In our case, the number of groups equals the number of companies. When the number of instruments surpasses the number of groups, the model may encounter overidentification issues, which would require a reduction in the number of instruments. This condition arises when the moment conditions provide more information than is necessary for the estimation.

Both the Hansen and Sargan tests indicate if a given model is correctly specified and if the instruments are valid (Ullah et al., 2018). However, when running two-step system GMM, relying on a Hansen test is sufficient, because it uses an optimal weighting matrix. This matrix accounts for autocorrelation and heteroscedasticity of the error terms, but the Sargan test is not based on this in a system GMM model (Roodman, 2009). For the Hansen test, rejecting the null hypothesis means that the model is not correctly specified and that the instruments are invalid. If it is not rejected the instruments are valid and exogenous.

Consider the following hypotheses:

$$H_0: Overidentification\ restrictions\ are\ valid.$$

$$H_1: Overidentification\ restrictions\ are\ not\ valid.$$

Roodman (2009) suggests that adhering strictly to a significance level of 0.05 may not be sufficient, and that significance levels up to 0.1 should also be considered with concern. It is important to note that these significance thresholds are indicative and not absolute, meaning that the context and purpose of a study should be carefully considered before determining the appropriate significance levels.

4.3.3 Arellano-Bond tests for autocorrelation

The Arellano-Bond tests are used to reveal first-order and second-order autocorrelation in panel data models (Arellano & Bond, 1991). To detect first-order autocorrelation, *AR(1)*, the test is run on the first-differences of the errors. The second-order autocorrelation, *AR(2)*, provides information about autocorrelation in levels, and the *AR(2)* test is therefore considered more important than *AR(1)* (Mileva, 2007).

For the *AR(1)* test, the null hypothesis should be rejected at the 0.05 significance level, uncovering first-order autocorrelation. The reason for this is the lagged variables. For the *AR(2)* test, the null hypothesis should be accepted at the 0.05 significance level, indicating no second-order autocorrelation. This is because the instruments become invalid with higher order autocorrelation (Arellano & Bond, 1991).

4.4 Presentation of models

Consider the following equation of a general dynamic econometric model, with two lags of the dependent variable:

$$y_{it} = \alpha + y_{it-1} + y_{it-2} + x_{it} + d_t + i_i + q_i + u_{it} \quad (3)$$

Where y_{it} is the dependent variable, representing the measurement of financial performance. α is the constant term. y_{it-1} is the one-year lagged version of the dependent variable, while y_{it-2} is the two-year lagged version. x_{it} is the explanatory variables. i_i is the industry-dummies, that capture industry-specific effects. d_t is the time-dummies, which capture the time-specific effects. q_i controls for unobserved heterogeneity. u_{it} is the error term, representing random disturbance.

Inserting our variables into equation (3) gives the following models:

$$ROA_{it} = L1ROA_{it} + L2ROA_{it} + R\&D\ Intensity_{it} + L1INT_{it} + L2INT_{it} + Size_{it} + Deratio_{it} + Year_t + Industry_i + q_i + u_{it}$$

$$Tobin's\ Q_{it} = L1TOBQ_{it} + L2TOBQ_{it} + R\&D\ Intensity_{it} + L1INT_{it} + L2INT_{it} + Size_{it} + Deratio_{it} + Year_t + Industry_i + q_i + u_{it}$$

where:

ROA = Return on Assets
L1ROA = Return on Assets with a 1-year lag
L2ROA = Return on Assets with a 2-year lag
Tobin's Q = Tobin's Q
L1TOBQ = Tobin's Q with a 1-year lag
L2TOBQ = Tobin's Q with a 2-year lag
R&D Intensity = Research & Development Intensity
L1INT = Research & Development Intensity with a 1-year lag
L2INT = Research & Development Intensity with a 2-year lag
Size = Natural logarithm of revenue
Deratio = Debt-to-equity ratio
Year = Year-dummies for all 17 years
Industry = Industry-dummies for all industries

The one-year and two-year lagged versions of the dependent variables are placed on the right-hand side of the models. The lagged versions of R&D Intensity are also included in each model. The lagged variables are used to capture the dynamic interrelatedness between the variables of the model.

4.5 Stata regression syntax

To give a better understanding of the technical aspect behind our models and to allow our research to be repeatable, we will present how we ran our regression in Stata. We have added this section because we want to be transparent.

Syntax for the ROA model:

xtabond2 ROA L1ROA L2ROA RDIntensity L1INT L2INT Deratio Size Year Industry*, gmm(ROA RDIntensity Size Deratio, lag (2 4) collapse) iv(Year* Industry*) twostep robust small*

Syntax for the Tobin's Q model:

xtabond2 TobinsQ L1TOBQ L2TOBQ RDIntensity L1INT L2INT Deratio Size Year Industry*, gmm(TobinsQ RDIntensity size, lag (2 4) collapse) iv(Year* Industry*) twostep robust small*

4.5.1 The technical process:

After the processing stage described in the data chapter, we generated unique identifiers for each company. This allowed us to use the "*xtset id Year"*-command to structure the dataset as a panel. To mitigate the risk of cross-group correlation, we also generated year-dummies from *Year* (Roodman, 2009).

After structuring the dataset and ensuring that all necessary variables were included, we executed the "*xtabond2*" command using the variables and specifications detailed above. This informs Stata that we are running a GMM regression. The system GMM approach is the default with this command.

The first variable in the syntax is the dependent variable of each model, while the others are the independent variables. *Year** is a "short-cut" that relieves us of having to write every year-dummy into the syntax. The same applies for *Industry**.

The variables inside the *gmm*-bracket are the variables we expect to be endogenous. *lag (2 4)* is a specification of how recent and distant the lags that are generated of the variables inside the *gmm*-bracket can be. Because we expect these variables to be endogenous, Wintoki et al.

(2012) suggest that the most recent lag should be at least two years. Because the number of instruments should not exceed the number of groups, we limited the most distant lags to four years. This limitation was discovered by testing different "lag-intervals". *collapse* is an option that further limits the number of instruments generated (Roodman, 2009). The *iv*-bracket contains variables expected to be exogenous, which in our case are *Year** and *Industry**, because these are completely independent of the model.

At the end of the syntax, we have added three options. *twostep* specifies the use of FEGMM (Fixed Effects General Method of Moments). *robust* triggers the Windmeijer correction. *small* gives t-test and F-test statistics instead of z-test and Wald χ^2 test (Roodman, 2009).

Note that the *Deratio* variable was included in the *gmm*-bracket for the *ROA* model, but not for the *Tobin's Q* model. This is because the *Tobin's Q* model produced poor test-statistics, indicating that our model was not correctly specified, until *Deratio* was removed from the bracket. Because the models use two different measures of financial performance, the basis for the assumption of *Deratio* being endogenous is different.

5.0 Empirical Results

In this chapter the regression results from the two models are presented. The first model has *ROA* as the dependent variable, while the second model has *Tobin's Q*. At first, the relevant test results are analyzed, before the coefficient estimates are interpreted. The OLS and Fixed Effects regressions are also presented, but these will not be further interpreted in accordance with the reasoning from the methodology chapter (section *4.2 OLS & Fixed* Effects). The interpretations of the coefficients are under the assumption that all else is held equal.

5.1 The ROA model

Table 5.1: The ROA model.

ROA	OLS	Fixed Effects	System GMM
L1ROA			0.2954881
			(0.013)
L2ROA			-0.053823
			(0.702)
R&D Intensity	-0.0233689	0.0094958	-0.0753371
	(0.019)	(0.336)	(0.003)
L1INT	-0.0252678	-0.0115343	0.0391004
	(0.014)	(0.181)	(0.076)
L2INT	-0.0241253	-0.0044616	-0.184388
	(0.012)	(0.621)	(0.001)
Deratio	-0.0066468	-0.0039609	0.215858
	(0.013)	(0.087)	(0.323)
Size	0.037485	0.0686649	-0.03356613
	(0.000)	(0.000)	(0.366)
_cons	-0.2315764	-0.530724	0.2592799
	(0.003)	(0.000)	(0.477)
No. of observations	577	577	577
No. of instruments			41
No. of companies	51	51	51
R-squared	0.2688	0.1582	
Adjusted R-squared	0.2301		
AR(1)			0.038
AR(2)			0.694
Hansen			0.943
Sargan			0.889
F-statistic	0.000	0.000	0.000

This table shows the coefficients and their corresponding p-values (in brackets) of the OLS, Fixed Effects and the System GMM regression with ROA as the dependent variable.

The *AR(1)* test reveals a significant p-value of 0.038, confirming the anticipated presence of first-order autocorrelation. The *AR(2)* test yields a p-value of 0.694, indicating that the null hypothesis is not rejected, thereby establishing that there is no second-order autocorrelation in the model. In terms of instrument validity, the Hansen test produces a p-value of 0.943, signifying that the instruments are valid and that the model is robust, albeit weakened by many instruments. The number of instruments is however smaller than the number of groups, indicating that there is not an overidentification problem.

According to the estimation results, an increase of one unit in the lagged one-year return on assets (*L1ROA*) is associated with a corresponding increase of 0.2954 units in the current *ROA*, at a 5% significance level. *R&D Intensity* demonstrates a negative effect on *ROA*, being significant at a 1% level. An increase of one unit in *R&D Intensity* is estimated to decrease *ROA* by 0.0753 units. On the other hand, the lagged one-year R&D intensity (*L1INT*) shows a significant positive effect on *ROA*. It is however only significant at a 10% level. An increase of one unit in *L1INT* is estimated to increase *ROA* by 0.0391 units. Contrary to the positive one-year lag, the two-year lagged R&D intensity (*L2INT*) has a significant negative impact on *ROA* at a 1% level. When *L2INT* is increased by one unit, *L2INT* is estimated to decrease *ROA* by 0.0184 units.

5.2 The Tobin's Q model

Table 5.2: The Tobin's Q model.

Tobin's Q	OLS	Fixed Effects	System GMM
L1TOBQ			1.338159
			(0.000)
L2TOBQ			-0.0324732
			(0.786)
R&D Intensity	0.0144632	0.0796004	1.085731
	(0.877)	(0.428)	(0.021)
L1INT	0.17757	0.1985152	0.3121123
	(0.067)	(0.024)	(0.081)
L2INT	0.1332279	0.0816178	-0.3732675
	(0.139)	(0.374)	(0.000)
Deratio	-0.0139786	-0.016214	0.5932559
	(0.578)	(0.491)	(0.119)
Size	-1.962445	0.1232657	2.212252
	(0.000)	(0.298)	(0.008)
_cons	4.110278	2.583828	-23.28482
	(0.000)	(0.012)	(0.004)
No. of observations	577	577	577
No. of instruments			37
No. of companies	51	51	51
R-squared	0.3687	0.0251	
Adjusted R-squared	0.3352		
AR(1)			0.038
AR(2)			0.874
Hansen			0.997
Sargan			0.967
F-statistic	0.000	0.000	0.000

This table shows the coefficients and their corresponding p-values (in brackets) of the OLS, Fixed Effects and the System GMM regression with Tobin's Q as the dependent variable.

The *AR(1)* test yields a p-value of 0.038, providing evidence for the presence of first-order autocorrelation. The *AR(2)* test gives a p-value of 0.874, entailing that the null hypothesis of second-order autocorrelation is not rejected. Moving on to the Hansen test, its p-value of 0.997 supports the validity of the instruments used in the model, ensuring its robustness. Although the model is weakened by many instruments, the number of groups are still higher, indicating the absence of an overidentification problem.

Regarding the regression results, the one-year lagged Tobin's Q (*L1TOBQ*) is significant at the 1% level, with a coefficient of 1.3382. An increase of one unit in *L1TOBQ* results in an estimated increase of 1.3382 units in *Tobin's Q.* The current year's *R&D Intensity* has a positive effect on *Tobin's Q* at the 5% level, with an estimated coefficient of 1.0857. The one-year lagged R&D intensity (*L1INT*) is also positive and significant, albeit at the 10% level, with a coefficient of 0.3121. However, the coefficient of *R&D Intensity* lagged two years (*L2INT*) is negative and significant at the 1% level, with an estimated decrease of 0.3732 units in *Tobin's Q* following a one unit increase of *L2INT*. Lastly, *Size* is significant at the 1% level, with an estimated increase of 2.2123 units in *Tobin's Q* following a one unit increase in *Size*.

6.0 Discussion

We begin this chapter by discussing our hypothesis on the short-term financial performance in relation to our results and prior literature. Thereafter, we continue the discussion in the same way regarding our hypothesis on the long-term financial performance.

6.1 Short-term financial performance

The first research hypothesis (H_1) of this study suggested that R&D investments have a negative short-term effect on financial performance. Our results affirm this hypothesis by showing a negative relation between the current year *R&D Intensity* and *ROA*. Similar to other types of investment, R&D is expected to have a delayed positive impact on operational performance. While an investment may have an overall positive net present value, it typically has a negative impact on operating performance during the initial stages of its lifetime. The negative relationship observed is consistent with the findings of Vithessonthi & Racela (2016), Alam et al. (2020) and Chen et al. (2019), who also highlight the same impact on operational performance.

The results also indicate that the negative effect from the year of investment is prolonged. We argue that the negative two-year lagged *R&D Intensity* can be a result of two things: failed investments and a spillover effect. Firstly, failed R&D investments cannot directly contribute positively to a company's operations. Furthermore, as these investments typically are immaterial and have limited alternative use, the resale value is likely to be non-existent, or at least very low. As a consequence, the risk associated with R&D is higher compared to material investments. Secondly, companies that invest in R&D are vulnerable to a spillover effect, whereby non-investing companies harvest benefits without incurring the associated costs. This cynicism may create an illusion of a negative effect between R&D expenditure and operating performance for the investing companies. It is a possibility that this is the cause of the negative relationship we found.

Effective resource allocation is a crucial contributor to a company's success. According to Lin et al. (2006), commercial orientation is essential to achieving success from R&D investments. Therefore, to maximize the value generated from R&D investments, it is imperative for a company to adopt a solid strategic approach to allocate its resources. This approach should ensure that R&D investments are commercially oriented, which can help to generate value and enhance its competitive advantage in the market. However, extensive grants and financial schemes provided by the government could lead to principal-agent problems where the interests of managers and owners may not be aligned. This could potentially hinder the strategic approach of an investment, reducing the probability of success. While a government-supported R&D investment could provide major benefits for a company and its managers, a failed R&D investment could result in financial losses that are shared with the government. Therefore, it is important for companies to balance their R&D investment decisions with careful consideration of the potential risks and rewards involved.

Our findings indicate that there is a positive dynamic relationship between the one-year lagged *ROA* and the current year *ROA*. This suggests that a company's financial performance has a degree of persistence. If previous financial performance affects the level of *R&D Intensity*, it is plausible that *L1ROA* indirectly affect *ROA* through *R&D Intensity*. In this case, the past realizations of *ROA* may therefore influence current year *R&D Intensity*.

While R&D investments may lead to negative short-term financial performance, we do not suggest that companies should avoid such investments solely because of this aspect. The output of R&D can be an important contributor to a company's competitiveness and survival, regardless of whether the short-term returns are positive or negative. Therefore, it is essential to discuss the long-term effects of such investments.

6.2 Long-term financial performance

The second research hypothesis (H_2) of this study stated that R&D investments have a positive long-term effect on financial performance. Our findings from the *Tobin's Q* model provide empirical support for this hypothesis, demonstrating a positive relation between *Tobin's Q* and *R&D Intensity* in the current year. This immediate effect aligns with the findings of Connolly & Hirschey (2005), indicating that the market recognizes and acknowledges an R&D investment. An immediate increase in *Tobin's Q* demonstrate that there has been an increase in the equity's market value, reflecting heightened expectations for future earnings and profitability following the investment. This is similar to the explanation provided by Szewczyk et al. (1996) and Donelson & Resutek (2012).

The one-year lagged *R&D Intensity* also has a positive, but weak effect on *Tobin's Q*. This conveys that the positive effect on market performance is reduced one year after the investment, but is also evidence of the time it takes for the investment to materialize. However, our findings show a negative impact of the two-year lagged *R&D Intensity* on *Tobin's Q.* This may be attributed to the company's strategic approach and the failure of past R&D investments. Hence, it appears that the market no longer recognizes any value from these investments. While the impact of *R&D Intensity* on *Tobin's Q* eventually becomes negative after two years, the accumulated effect remains positive. Moreover, this effect would be enhanced with consecutive years of investments.

From the descriptive statistics presented in *Table 3.3*, we observe that the *R&D Intensity* of our sample exceeds a lower threshold presented by Morbey (1988) and Wang (2011). These studies contend that companies which consistently surpass the threshold in R&D investment attain sustained long-term financial growth. The stability of the *R&D Intensity* for the companies in our sample supports their capability to generate long-term growth in market performance. On the other hand, the non-linear relationship between R&D expenditure and market performance highlighted by Jaisinghani (2016) and Pantagakis et al. (2012) implies an upper threshold as well. Given that some of the companies in our sample have a high *R&D Intensity*, there is a risk of exceeding the upper threshold, which could have adverse implications for the relationships we have identified.

While our results suggest that investors may be overvaluing R&D investments, it should be noted that prior literature has consistently demonstrated a positive and lasting effect of R&D expenditure on *Tobin's Q*, in addition to market value and stock returns, which are highly related to *Tobin's Q*. Nevertheless, it is possible that investors are not fully accounting for the risk associated with such investments, which could lead to overvaluation.

Our regression results prove that company size has a positive connection with *Tobin's Q*. This supports the conclusion of Ibhagui (2019), where larger companies benefit more from *R&D Intensity* than smaller companies, when the relation with financial performance is positive. Connolly & Hirschey (2005) argue that larger companies are more effective with R&D expenditure, supplementing the conclusion of Ibhagui (2019). We argue that larger companies have three competitive advantages. Firstly, economies of scale allows for more efficient production and distribution. Secondly, a greater market share facilitates effective marketing of their products and services. Thirdly, access to resources in terms of financing and human capital allows a larger company to capitalize on investment opportunities, while also being more resilient to failed investments.

7.0 Conclusion

The problem statement of this thesis is "*What is the effect of R&D investments on the financial performance of companies listed on the Oslo Stock Exchange?*". In order to address this problem, we formulated and answered two research hypotheses concerning both short-term and long-term financial performance. We found that R&D investments have a negative short-term effect which turns positive in the long-term. We contend that the negative short-term effect stems from the absence of immediate returns that can offset the rising operating costs. However, we argue that the market expects these investments to benefit the company over time, which explains the positive long-term effect.

The objective of this thesis is to provide a better understanding of the importance regarding R&D investments on financial performance for companies listed on the Oslo Stock Exchange. Our broad approach, encompassing diverse industries and company types, contributes to make our study more generalizable compared to previous research that focused solely on specific company types within particular industries. Our findings demonstrate the existence of a dynamic relationship between the variables, which gives rise to endogeneity issues. To ensure the validity and reliability of our results, we employ a System GMM approach to address the dynamic relations and the problems of endogeneity.

Our findings carry significant implications for investors, companies, policymakers, and academia alike. For investors, our study underscores the importance of adopting a long-term perspective when making investment decisions, considering the demonstrated impact of R&D investments on financial performance. For companies, we have emphasized the importance of investing sufficiently into R&D while also being commercially oriented and strategically allocating resources. The observed negative short-term effects followed by positive long-term effects further highlight the role of policymakers in designing and implementing grants and financial schemes that encourage R&D investments. For academia, our thesis contributes to the existing literature by examining an exchange that has not been researched comprehensively regarding R&D and financial performance, laying the foundation for further research.

8.0 Further research

This thesis does not directly evaluate the success of innovative projects; therefore, it would be interesting to research a possible connection between our findings and data that incorporates the specific input/output relationship between R&D and financial performance. This could be done by gathering data on patents, thereby matching the R&D input with output.

To enhance the comprehensiveness of our results, it would be beneficial to incorporate additional time lags, capturing the prolonged effects further into the future. This analysis has primarily focused on proxies for future outcomes rather than the actual future data.

It is important to note that our analysis has excluded companies that do not allocate resources to R&D expenditure. To gain a more nuanced perspective, future research could consider including non-investing companies, and partitioning the sample into portfolios based on factors such as R&D Intensity or size. Additionally, utilizing other metrics for financial performance and relevant control variables could further enrich our findings.

Lastly, gaining an increased understanding of the causal relationship on R&D and financial performance would be very valuable for company stakeholders. It could discern the underlying factors that drive the relationship between R&D investments and financial performance, filling a large gap in the literature.

References

- Abdallah, W., Goergen, M. and O'Sullivan, N. (2015) Endogeneity: How Failure to Correct for it can Cause Wrong Inferences and Some Remedies, *British Journal of Management*, 26(4), pp.791–804. Available from: https://doi.org/10.1111/1467-8551.12113
- Alam, A., Uddin, M., Yazdifar, H., Shafique, S. and Lartey, T. (2020) R&D investment, firm performance and moderating role of system and safeguard: Evidence from emerging markets, *Journal of Business Research*, 106 (1), pp. 94-105. Available from: https://doi.org/10.1016/j.jbusres.2019.09.018
- Anagnostopoulou, S. C and Levis, M. (2006) R&D and performance persistence: Evidence from the United Kingdom, *City University: Cass Business School*. Available from: https://www.researchgate.net/publication/228539030_RD_and_Performance_Persistence_Evidence_from_the_UK
- Arellano, M. and Bond, S. (1991) Some Test of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, *The Review of Economic Studies*, 58 (2), pp. 277-297. Available from: https://www.jstor.org/stable/2297968
- Baum, C., F., Schaffer, M.E. and Stillman, S. (2003) Instrumental Variables and GMM: Estimation and Testing, *The Stata Journal: Promoting communications on statistics and Stata*, 3 (1), pp. 1–31. Available from: https://doi.org/10.1177/1536867x0300300101
- Blanco, L., R., Gu, J. and Prieger, J., E. (2016) The impact of Research and Development on Economic Growth and Productivity in the U.S. States, *Southern Economic Journal*, 82 (1), pp. 914-934. Available from: https://doi.org/10.1002/soej.12107
- Blundell, R. and Bond, S. (1998) Initial conditions and moment restrictions in dynamic panel data models, *Journal of Econometrics*, 87 (1), pp. 115-143. Available from: https://www.sciencedirect.com/science/article/pii/S0304407698000098
- Børing, P. and Mark, M., S. (2022) Public R&D support to enterprises in four R&D sectors: the mix of types of aid and policy agencies, *International Review of Applied Economics*. Available from: https://doi.org/10.1080/02692171.2022.2138835
- Chambers, D., J., Jennings, R. and Thompson, R., B. (2002) Excess Returns to R&D-Intensive Firms, *SSRN*. Available from: http://dx.doi.org/10.2139/ssrn.299159

- Chan, L., K., C., Lakonishok, J. and Sougiannis, T. (2001) The Stock Market Valuation of Research and Development Expenditures, The Journal of Finance, 56 (6), pp. 2431-2456. Available from: https://doi.org/10.1111/0022-1082.00411
- Chen, T., Guo, D.-Q., Chen, H.-M. and Wei, T. (2019) Effects of R&D intensity on firm performance in Taiwan's semiconductor industry, *Economic Research-Ekonomska Istraživanja*, 32 (1), pp. 2377–2392. Available from: https://doi.org/10.1080/1331677x.2019.1642776
- Connolly, R., A. and Hirschey, M. (2005) Firm size and the effect of R&D on Tobin's Q, *R&D Management*, 35 (2), pp. 217-223. Available from: https://doi.org/10.1111/j.1467-9310.2005.00384.x
- Donelson, D., C. and Resutek, R. J. (2012) The effect of R&D on future returns and earnings forecasts, *Review of Accounting Studies*, 17 (4), pp. 848–876.Available from: https://doi.org/10.1007/s11142-011-9179-y
- Eberhart, A., C., Maxwell W., F. and Akhtar, A., R. (2004) An Examination of Long-Term Abnormal Stock Returns and Operating Performance Following R&D Increases, The Journal of Finance, 59 (2), pp. 623-650. Available from: https://www.jstor.org/stable/3694909
- Ehie, I., C. and Olibe, K. (2010) The effect of R&D investment on firm value: An examination of US manufacturing and services industries, *International Journal of Production Economics*, 128 (1), pp. 127-135. Available from: https://doi.org/10.1016/j.ijpe.2010.06.005
- Euronext (2023). *Oslo Børs Benchmark Index GI*. Available from: https://live.euronext.com/nb/product/indices/NO0007035327-XOSL
- Gompers, P., Ishii, J. and Metrick, A. (2003) Corporate Governance and Equity Prices, *The Quarterly Journal of Economics*, 118 (1), pp. 107-156. Available from: https://doi.org/10.1162/00335530360535162
- Gormley, T., A. and Matsa, D., A. (2013) Common Errors: How to (and Not to) Control for Unobserved Heterogeneity, Review of Financial Studies, 27 (2), pp. 617–661. Available from: https://doi.org/10.1093/rfs/hht047
- Hammervold, R. (2020) Paneldata. *Multivariate analyser med Stata: en kort innføring*. First edition. Bergen: Fagbokforlaget, pp. 164-176.
- Hansen, L., P. (1982) Large Sample Properties of Generalized Method of Moments Estimators, *Econometrica*, 50 (4), pp. 1029-1054. Available from: https://doi.org/10.2307/1912775

- Hou, K., Hsu, P.-H., Wang, S., Watanabe, A. and Xu, Y. (2022) Corporate R&D and Stock Returns: International Evidence, *Journal of Financial and Quantitative Analysis*, Cambridge University Press, 57 (4), pp. 1377–1408.
- Ibhagui, O. (2019) Do large firms benefit more from R&D investment?, *The European Journal of Applied Economics*, 16 (2), pp. 155–173. Available from: https://doi.org/10.5937/ejae16-21770
- Jaisinghani, D. (2016) Impact of R&D in profitability in the pharma sector: an empirical study from India, *Journal of Asia Business Studies*, 10 (2), pp. 194-210. Available from: https://doi.org/10.1108/JABS-03-2015-0031
- Kaplan, S., N. and Zingales, L. (1997) Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?, *The Quarterly Journal of Economics*, 112 (1), pp. 169-215. Available from: https://doi.org/10.1162/003355397555163
- Koh, P.-S. and Reeb, D., M. (2015) Missing R&D, *Journal of Accounting and Economics*, 60 (1), pp. 73–94. Available from: https://doi.org/10.1016/j.jacceco.2015.03.004.
- Kutner, M., H., Nachtsheim, C., J and Li, W. (2005) *Applied linear statistical models*, fifth edition. New York: McGraw-Hill.
- Lee, J., W. (2020) Lagged Effects of R&D Investment on Corporate Market Value: Evidence from Manufacturing Firms Listed in Chinese Stock Markets, *Journal of Asian Finance Economics and Business*, 7 (8), pp. 69-76. Available from: *https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4035105*
- Lee, M. and Choi, M. (2015) The Relationship between R&D investment and Ownership Structure in KOSDAQ Pharmaceutical Firms, *The Journal of the Korea Contents Association*. Available from: https://koreascience.kr/article/JAKO201520441373453.page
- Lev, B. and Sougiannis, T. (1996) The capitalization, amortization, and value-relevance of R&D, *Journal of Accounting & Economics*, 21 (1), pp. 107-138. Available from: https://www.sciencedirect.com/science/article/pii/0165410195004106
- Li, J., Ding, H., Hu, Y. and Wan, G. (2021) Dealing with dynamic endogeneity in international business research, *Journal of International Business Studies*, 52 (1), pp. 339-362. Available from: https://ideas.repec.org/a/pal/jintbs/v52y2021i3d10.1057_s41267-020-00398-8.html
- Lin, B.-W., Lee, Y. and Hung, S.-C. (2006) R&D intensity and commercialization orientation effects on financial performance, *Journal of Business Research*, 59 (1), pp. 679-685. Available from: https://doi.org/10.1016/j.jbusres.2006.01.002

- Meld. St. 4 (2018-2019) (2019) Long-term plan for research and higher education 2019-2028. Oslo: Norwegian Ministry of Education and Research.
- Mileva, E. (2007) Using Arellano-Bond Dynamic Panel GMM Estimators in Stata, *Economics Department*, 64 (1). New York: Fordham University, pp. 1-10.
- Morbey, G., K. (1988) R&D: Its Relationship to Company Performance, *Journal of Product Innovation Management*, 5 (3). Available from: https://doi.org/10.1111/1540-5885.530191
- Pantagakis, E., Terzakis, D. and Arvanitis, S. (2012) R&D Investments and Firm Performance: An Empirical Investigation of the High Technology Sector (Software and Hardware) in the E.U., *SSRN*. Available from: http://dx.doi.org/10.2139/ssrn.2178919
- Regnskapsloven (2023). Art 4. Konsernregnskap for selskaper med offentlig omsatte verdipapirer, *Lov om årsregnskap m.v.* Available from: https://lovdata.no/dokument/NL/lov/1998-07-17-56?q=regnskapsloven
- Roberts, M., R. and Whited, T., M. (2013) Chapter 7 - Endogeneity in Empirical Corporate Finance, Constantinides, G., M., Harris, M. and Stulz, R., M. (editors), *Handbook of the Economics of Finance*, 2 (A). Amsterdam: Elsevier, pp. 493-572.
- Roodman , D. (2009) How to do Xtabond2: An Introduction to Difference and System GMM in Stata, *The Stata Journal*, 9 (1), pp. 86-136. Available from: https://journals.sagepub.com/doi/10.1177/1536867X0900900106
- Tsai, K.-H. and Wang, J.-C. (2005) Does R&D performance decline with firm size?—A re-examination in terms of elasticity, *Research Policy*, 34 (6), pp. 966–976. Available from: https://doi.org/10.1016/j.respol.2005.05.017
- Semadeni, M., Withers, M. and Certo, S., T. (2014) The perils of endogeneity and instrumental variables in strategy research: Understanding through simulations, *Southern Medical Journal*. Available from: https://www.semanticscholar.org/paper/The-perils-of-endogeneity-and-instrumental-in-%3A-Semadeni-Withers/d3455f07e9f9c9bc6baf40a86fc6c1b20d7b34f1
- Shah, S., Z., A., Liang, S. and Akbar, S. (2013). International Financial Reporting Standards and the value relevance of R&D expenditures: Pre and post IFRS analysis, *International Review of Financial Analysis*, 30 (1), pp. 158-169. Available from: https://doi.org/10.1016/j.irfa.2013.08.001
- Sokolov-Mladenović, S., Cvetanović, S. and Mladenović, I. (2016) R&D expenditure and economic growth: EU28 evidence for the period 2002–2012, *Economic Research-*

Ekonomska Istraživanja, 29 (1), pp. 1005-1020. Available from: https://doi.org/10.1080/1331677X.2016.1211948

- Sougiannis, T. (1994) The Accounting Based Valuation of Corporate R&D, *The Accounting Review*, 69 (1), pp. 44-68. Available from: https://www.jstor.org/stable/248260
- Stock, J., H., Wright, J., H. and Yogo, M. (2002) A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments, *Journal of Business and Economic Statistics*, 20 (4), pp. 518-529. Available from: https://www.tandfonline.com/doi/pdf/10.1198/073500102288618658?needAccess=true&role=button
- Szewczyk, S., H., Tsetsekos, G., P. and Zantout, Z. (1996) The Valuation of Corporate R&D Expenditures: Evidence from Investment Opportunities and Free Cash Flow, *Financial Management*, 25 (1), 1996, pp. 105–110. Available from: https://www.jstor.org/stable/3665906
- Ullah, S., Akhtar, P. and Zaefarian, G. (2018) Dealing with endogeneity bias: The generalized method of moments (GMM) for panel data, *Industrial Marketing Management*, 71 (1), pp. 69-78. Available from: https://www.sciencedirect.com/science/article/pii/S0019850117308532
- Vithessonthi, C. and Racela, O., C. (2016) Short- and long-run effects of internationalization and R&D intensity on firm performance, *Journal of Multinational Financial Management*, 34 (1), pp. 28–45. Available from: https://doi.org/10.1016/j.mulfin.2015.12.001
- Wang, C.-H. (2011) Clarifying the Effect of R&D on Performance: Evidence from the High Technology Industries, *Asia Pacific Management Review*, 16 (1), pp. 51-64. Available from: https://www.researchgate.net/publication/268050075_Clarifying_the_Effects_of_RD_on_Performance_Evidence_from_the_High_Technology_Industries
- Wendt, K., K., Langhoff, K., Sarpebakken, B. and Østby, M., N. (2022). Lite vekst i utgiftene til forskning og utvikling. (SSB-rapport 10/2022) Oslo: SSB. Available from: SSB introduksjonskapittel: https://www.ssb.no/teknologi-og-innovasjon/forskning-og-innovasjon-i-naeringslivet/artikler/lite-vekst-i-utgiftene-til-forskning-og-utvikling
- Wintoki, M., B., Linck, J., S. and Netter., J., M. (2012) Endogeneity and the dynamics of internal corporate governance, *Journal of Financial Economics*, 105 (3), pp. 581-606. Available from: https://www.sciencedirect.com/science/article/pii/S0304405X12000426

- Wooldridge, J., W. (2002) *Econometric Analysis of Cross Section and Panel Data*. First edition. Cambridge: The MIT Press.
- Zhu, Z. and Huang, F. (2012) The Effect of R&D Investment on Firms' Financial Performance: Evidence from the Chinese Listed IT Firms, *Modern Economy*, 3 (8), pp. 915-919. Available from: http://dx.doi.org/10.4236/me.2012.38114

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