NHH

Norwegian School of Economics
Bergen, Spring 2023

Derivative Usage and Firm Value

Evidence for Norwegian Non-financial Firms

Jun He, Philip Ingebrigtsen

Supervisor: Jørgen Haug

Master thesis, Economics and Business Administration

Major: Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

This thesis was written as a part of the Master of Science in Economics and Business Administration at NHH. Please note that neither the institution nor the examiners are responsible – through the approval of this thesis – for the theories and methods used, or results and conclusions drawn in this work.

Acknowledgements

This dissertation serves as the culmination of our two-year Finance Major journey at the Norwegian School of Economics (NHH), thereby rounding off our Master of Science and Business Administration degree.

Our curiosity was piqued early on to identify a compelling subject relative to derivatives, leading us to asset investment and management. This intriguing topic offered the opportunity to utilize and extend the knowledge we've acquired throughout the diverse courses that make up our major. Though working on this dissertation presented its share of challenges, it was also a gratifying endeavor.

We would like to thank our supervisor, associate professor Jørgen Haug, for invaluable guidance and support in every step of the process. The thesis would not have its current measure of quality without his expertise and advice. We would also like to thank Per Fossan-Waage, head of Deloitte's Capital Market Services, for the original thesis idea proposal and assistance along the way. We are grateful for the help, meetings and discussions carried out.

Lastly, we want to extend our appreciation to our families and friends. Their unwavering support has been instrumental in completing this pivotal stage of our studies at NHH.

Norwegian School of Economics

Bergen, May 2023

Jun He

Philip Ingebrigtsen

Abstract

Using derivative usage data from 185 firms listed on the Oslo Exchange during the 2007 to 2021 time period, we find a positive correlation between derivative usage and firm value. However, the significance varies across derivative types and firm value quantile distributions. The derivative instruments exhibit varying associations with firm values that are mostly positive, though interest rate cap derivatives generally show negative associations. Also, there are dynamic associations between derivative usage and firm value over different time intervals. These results are robust to dynamic difference-in-difference estimations, an econometric framework that reduces potential endogeneity problems and explains causality. We conclude that derivative usage has, in general, a positive lagged impact on firm value for Norwegian-listed firms that are exposed to the relevant risks.

Keywords – Corporate hedging, Derivative usage, Firm valuation

Contents

1 Introduction **1**

2 Background **4**
2.1 Derivative Usage and Firm Value 4
2.2 Lagged Influence of Derivatives 5

3 Data **7**
3.1 Data Collection 7
3.2 Dependent Variables 8
3.2.1 Tobin's Q 8
3.3 Risk Exposures 8
3.3.1 Any Risk Exposure 8
3.3.2 Floating Interest Rate Exposure 9
3.3.3 Foreign Exchange Exposure 9
3.3.4 Commodity Exposure 10
3.4 Independent Variables 10
3.4.1 Derivative Usage 10
3.4.2 Interest Rate Derivatives 11
3.4.3 Foreign Exchange Derivatives 11
3.4.4 Commodity Derivatives 11
3.5 Control Variables 11
3.5.1 Return on Assets 11
3.5.2 Leverage 12
3.5.3 Current Ratio 12
3.5.4 Liquidity 12
3.5.5 Tangibility 13
3.5.6 Firm Size 13
3.5.7 Industry 13
3.6 Descriptive Statistics 13

4 Methodology **18**
4.1 Benchmark Regression 18
4.2 Quantile Regression 19
4.3 Difference-in-Difference: Event Study 21

5 Analysis **24**
5.1 Baseline and Quantile Regression 24
5.1.1 Derivative Usage 24
5.1.2 Interest Rate Derivative 26
5.1.3 Currency Derivative 28
5.1.4 Commodity Derivative 30
5.2 Instruments Heterogeneity Test 33
5.2.1 Derivative Instruments 33
5.2.2 Interest Rate Derivative Instruments 35
5.2.3 Currency Derivative Instruments 37
5.2.4 Commodity Derivative Instruments 39

5.3 Time Heterogeneity Test 41
5.3.1 Derivative Usage 41
5.3.2 Interest Rate Derivatives 43
5.3.3 Currency Derivatives 45
5.3.4 Commodity Derivatives 47
5.4 Difference-in-Difference: Event Study 49
5.4.1 Derivative Usage 49
5.4.2 Interest Rate Derivatives 52
5.4.3 Currency Derivatives 55
5.4.4 Commodity Derivatives 58
5.4.5 Placebo Test 61

6 Conclusion **63**
6.1 Empirical Contributions 63
6.2 Managerial Implications 64
6.3 Limitations and Future Research 65

References **66**

Appendix **68**
A1 Table of Variables 68
A2 List of Commodities 69
A3 Data-Set Plots 70
A4 Code Listings 80
A4.1 Stata: OLS and Quantile Regression 80
A4.2 R: Difference-in-Difference: Event Study 81

List of Figures

4.1 Quantile Distribution of Ln(Tobin's Q) 20
5.1 Difference-in-Difference event study on Derivative Usage 49
5.2 Difference-in-Difference event study on Interest rate Derivatives 52
5.3 Difference-in-Difference event study on Currency Derivatives 55
5.4 Difference-in-Difference event study on Commodity Derivatives 58
A3.1 Use of derivatives, by users and non-users, 2007–2021 70
A3.2 Use of derivatives, by types, 2007–2021 71
A3.3 Use of derivatives (types), by Industry, 2007–2021 72
A3.4 Use of derivatives (types), by period, 2007–2021 73
A3.5 Use of derivatives, by instruments, 2007–2021 74
A3.6 Use of derivatives (instruments), by industry, 2007–2021 75
A3.7 Use of derivatives (instruments), by period, 2007–2021 76
A3.8 Use of derivatives (types), by firm size, 2007–2021 77
A3.9 Use of derivative (types), by firm size, 2007–2021 78
A3.10 Use of derivatives (instruments), by firm size, 2007–2021 79

List of Tables

3.1 Industry Breakdown of Derivative Usage & Risk Exposure 14
3.2 Industry Breakdown of Derivative Usage & Risk Exposure by Risk 14
3.3 Derivative Instruments Usage & Percentage by Risk Exposure 15
3.4 Any Derivative Usage for Different Time Intervals 16
3.5 Derivative Usage by Risk Exposure for Different Time Intervals 16
3.6 Difference in Variables between Derivative Users and Non-users 17
5.1 Baseline and Quantile Regressions: Derivatives Usage 25
5.2 Baseline and Quantile Regressions: Interest Rate Derivatives 27
5.3 Baseline and Quantile Regressions: Currency Derivatives 29
5.4 Baseline and Quantile Regressions: Commodity Derivatives 32
5.5 Baseline and Quantile Regressions: Derivative Instruments 34
5.6 Baseline and Quantile Regressions: Interest Rate Derivative Instruments 36
5.7 Baseline and Quantile Regressions: Currency Derivative Instruments . . . 38
5.8 Baseline and Quantile Regressions: Commodity Derivative Instruments . 40
5.9 Baseline and Quantile Regressions: Derivatives Usage 42
5.10 Baseline and Quantile Regressions: Interest Rate Derivative 44
5.11 Baseline and Quantile Regressions: Currency Derivative 46
5.12 Baseline and Quantile Regressions: Commodity Derivative 48
5.13 DiD Event study: Staggered treatment (Derivative Usage) 51
5.14 DiD Event study: Staggered treatment (Interest Rate Derivative) 54
5.15 DiD Event study: Staggered treatment (Currency Derivative) 57
5.16 DiD Event study: Staggered treatment (Commodity Derivative) 60
5.17 DiD Event study: Staggered treatment (Placebo Test) 62
A1.1 Variables Used 68

1 Introduction

Derivative adoption for risk management has become increasingly common among firms. As per the Bank for International Settlements (BIS) latest statistics, global markets have seen a rising trend in total derivative contracts. This surge is partially attributed to firms leveraging these financial tools to counteract financial and operational risks. Despite the apparent uptick in derivative usage, the corporate finance academic community still needs to decide on the precise value addition of hedging activities to firms.

The efficient market hypothesis posits that a company's financial policies do not influence its value. Investors can mitigate the risks hedged by a firm by creating a diversified portfolio, negating the need for a hedging policy premium. However, relaxing some of the assumptions of Modigliani & Miller's (1958) theory allows us to demonstrate that a hedging policy might potentially increase firm value. Notably, studies by Allayannis & Weston (2001) and Panaretou (2014) found a positive correlation between hedging foreign currency risk and higher market values for US and UK firms. Hagelin et al. (2004) reported similar benefits for Swedish firms using derivatives. However, the impact of derivative usage on firm value remains unclear due to conflicting empirical findings. Guay (1999) found decreased interest rate volatility, but no significant market risk changes for non-financial firms using derivatives. Studies by Jin & Jorion (2004) and Xue et al. (2022) found no substantial relationship between commodity derivatives and market value for US oil and gas producers. Similarly, Clark et al. (2006) found no impact of currency derivative usage on firm value for French firms.

The Norwegian case is distinct in studying the effect of hedging activities on firm value due to its export-dependent economy. Macroeconomic volatility, particularly in exchange rates and exposure to fluctuating commodity prices, yields incentives to use derivatives for Norwegian firms, where hedging could yield significant benefits. This study scrutinizes 185 non-financial firms listed on the primary Oslo Børs and the secondary Euronext Expand equity markets from 2007 to 2021. It includes a variety of derivatives within Interest Rates, Foreign Exchange, and Commodity Prices and assesses their impact on Tobin's Q, which is an indicator of firm value. Derivative usage data were gathered primarily through textual analysis of annual reports, with risk exposure information manually collected.

This paper uniquely explores the effect of derivative usage on firm value when accounting for the underlying risk hedged by these derivatives. Innovative Quantile Regression and Dynamic Difference-in-Difference Models, rather than traditional OLS regressions, are used for a multifaceted examination of this issue.

First, over the past two decades, research has illuminated the effects of derivative usage on non-financial firms' value. However, unresolved questions persist, notably, whether derivatives impact firm value growth differently. This study aims to address this gap by assessing how the value effects of derivatives vary across interest rates, currency, and commodity derivatives. To enhance the robustness of our conclusions, we partition our dataset into subsets exposed to variable interest rates, fluctuating foreign exchange, or volatile commodity prices. Our focus is on non-financial firms using derivatives for risk management with the intent of value addition. Given the distributional imbalance of firms, we also aim to explore the varied effects on different types of firms, primarily classified by Tobin's Q. Utilizing quantile regressions, we aim to ascertain if the impact of derivatives is more pronounced in higher-valued firms compared to their lower-valued counterparts.

Second, we explore whether the value implications of derivatives are consistent and delayed, as effects may materialize with a delay. Typically, derivative contracts are long-term, providing a hedge against potential crises. We employ a novel methodology to analyze this dynamic relationship between derivative usage and firm value over time: dynamic difference-in-difference. Rather than viewing the effects of derivative usage as isolated events, we consider them part of firms' overall policy. We aim to discern the difference between usage periods (treated) and non-usage (non-treated). The findings will also enhance our understanding of managerial performance in using derivatives for hedging purposes.

The main findings of our study are as follows. OLS and quantile regression estimations consistently indicate a positive relationship between derivative usage and firm value, especially for firms with lower firm values or Tobin's Q. Interest rate and commodity derivatives exhibit a substantial relationship, whereas currency derivatives do not. However, the relationships vary across derivative instruments (e.g. Forwards, Options, Swaps, and Caps) and time intervals. The dynamic difference-in-difference model also shows positive effects from derivative usage. However, interest rate derivatives do not demonstrate significant effects; their impacts can even turn negative over a prolonged period. Conversely, currency and commodity derivatives potentially exhibit significantly positive effects after years of usage. In summary, derivatives with differing characteristics yield varied effects, but overall their influences are predominantly positive, especially currency and commodity derivatives with substantial impacts becoming evident over several years.

Our study is organized as follows: Part 2 reviews the relevant literature and formulates hypotheses. Part 3 presents the data used in this study, delineates dependent and independent variables, and offers summary statistics. Part 4 outlines the methodologies we employ. Part 5 provides the empirical results and analyzes the relationship between derivative usage and firm value. Lastly, Part 6 concludes the study, discussing its limitations and prospects.

2 Background

2.1 Derivative Usage and Firm Value

The theoretical literature suggests that derivative instruments are often implemented to tackle a multitude of market imperfections, but relatively fewer studies test for a direct relationship between the usage of derivatives and firm value. Graham & Smith (1999) show that corporate hedging with interest rate and foreign exchange derivatives increases the firm value and debt capacity. They identify tax incentives, underinvestment costs, financial distress costs, and firm size as the main drivers of corporate hedging. Allayannis (2001) found that firms with higher levels of foreign currency exposure tend to use more derivatives to manage their risk. In addition to these findings, Bartram et al. (2011) find that interest rate derivatives and currency derivatives can lower the expected value of costs associated with financial distress and increase the optimal debt-equity ratio, leading to a higher tax shield of debt and positive valuation effects as a result. According to Clark & Judge (2009), currency derivatives would increase firm value, but there is no hedging premium associated with foreign currency debt, except when combined with derivatives. Chen & King (2014) found that hedging reduces the cost of debt for firms, especially for those with higher earnings volatility and lower outside ownership. They also found support for the agency cost hypothesis, suggesting that hedging can mitigate conflicts between managers and shareholders. According to Kim et al. (2017), corruption negatively affects firm value and reduces the use of financial derivatives. However, the usage of financial derivatives has a positive impact on firm value, particularly in the post-global financial crisis period. Recently, Bachiller, Boubaker, & Mefteh-Wali (2021) found that the usage of derivatives has a positive effect on firm value, but results vary depending on the type of derivatives and the country of the firm.

Contrary to the aforementioned positive valuation effects, other researchers found different conclusions regarding the impact of derivative usage on valuation. Fauver & Naranjo (2010) found that derivative usage has a negative impact on firm value in firms with greater agency and monitoring problems. Lookman (2014) examines the impact of hedging on firm value in the oil and gas industry, specifically analyzing the effects of hedging big risks (commodity price volatility in the exploration & production segment) versus small risks (such as foreign exchange or interest rate risk). The study finds that hedging a big risk has a negative impact on firm value, while hedging a small risk has a positive impact. Additionally, the study considers agency conflict and managerial skill as potential factors and concludes that hedging does not significantly explain firm value after controlling for these factors. Recently, according to Ullah et al. (2023), their regression model shows that capital expenditures have a positive impact on firm value, while foreign exchange hedging has a negative impact.

In the context of Norway, there is only limited empirical evidence regarding the association between derivative usage and firm value. The most relevant study is done by Helland & Bjerkelund (2016), suggesting that currency hedging may not have a significant impact on financial outcomes in Norway. While earlier researchers investigated the possible channels through which derivatives could affect firm value, empirical studies on Norwegian firms have received little attention. Given Norway's heavy reliance on its export economy, it constitutes an essential subject for such investigations.

Building upon the literature on derivative usage and firm value, we hypothesize the following:

Hypothesis 1a. The value of firms exposed to variable interest rates, fluctuating foreign exchange rates, or volatile fluctuating commodity prices is positively correlated with their use of any type of derivative.

Hypothesis 1b. The value of firms exposed to variable interest rates is positively correlated with their usage of interest rate derivatives.

Hypothesis 1c. The value of firms exposed to fluctuating foreign exchange rates is positively correlated with their usage of currency derivatives.

Hypothesis 1d. The value of firms exposed to volatile commodity prices is positively correlated with their usage of commodity derivatives.

2.2 Lagged Influence of Derivatives

Given that the impact of derivative usage can take time to manifest and is not always immediately apparent, we also seek to account for the lagged effects of derivative usage. Bartram et al.'s study (2011) suggests that economic conditions can induce lagged effects on the benefits of derivative usage. However, this area necessitates further research. Thus, we anticipate the value effect of derivatives to become effective after their initial implementation, as consistent usage is likely essential for discerning their impact. This discussion culminates in our next hypothesis:

Hypothesis 2. The usage of derivatives has lagged positive effects for firm value growth after firms' first implementation.

3 Data

3.1 Data Collection

The data sample consists of all Norwegian non-financial firms currently listed on Norway's two main stock markets, namely the primary Oslo Børs and the secondary Euronext Expand, from 2007 to 2021. The exclusion of firms on the third market, Euronext Growth, is due to its lesser regulations regarding a listing that could lead to more extreme observations and outliers. Financial firms are also excluded as their incentives for using derivatives most likely differ from that of non-financial firms. Given that data for the accounting year of 2022 is not fully published until later into 2023, data for 2022 is also excluded. Accounting data is gathered through the Bloomberg Terminal, while market data is gathered through the Compustat database and Euronext website, and all numbers are reported in millions of Norwegian Kroners (NOK). All datasets are then merged. The final sample contains 1839 yearly observations at the firm level before the exploration of derivative usage. This is an unbalanced panel dataset of 185[1] firms over 15 years due to firms having different listing times.

Data on derivative usage is mainly collected with textual analysis, while risk exposure is mostly hand-collected from the 185 firms' annual reports. Firms are categorized as derivative users if they use at least one derivative for non-speculation purposes to hedge any uncertainty related to cash flows, whether operational or financial. The reports are thoroughly examined, and a firm is only classified as a user of derivatives if this is certain, as can be understood from the reports. Similar steps are taken to determine whether a firm is exposed to the underlying risk that the derivatives are supposed to hedge. The research question focuses on floating interest rates, foreign exchange (FX), and commodity price exposure. Thus, the derivative instruments considered are interest rate, FX, and commodity derivatives, respectively. Sub-classifications such as forwards, futures, options, and swaps are also collected in each of these main derivative groups. Forward freight agreements (FFAs), commonly used in the shipping sector, are not considered derivatives as they do not fall into any of the aforementioned categories and are incomparable to other sectors.

[1]We exclude firms that submitted their listing applications in 2021 but commenced trading in 2022.

Given that the dataset is partially hand-collected, it might include humanly made errors that cannot be fully eliminated. The process behind the data gathering is also made with human reasoning, and so both processes might have led to mistakes. The final dataset is proofread and controlled to be as precise and correct as possible.

3.2 Dependent Variables

A full list of definitions and calculations of the dependent-, independent-, and control variables to come can be found in Appendix A1.1.

3.2.1 Tobin's Q

This thesis employs Tobin's Q as the dependent variable and proxy for firm value, a prevalent continuous ratio used in this field's literature (e.g., Bartram et al., 2011; Santos et al., 2017; Kim et al., 2017). Comparable to Kim et al. (2017), Tobin's Q is constructed as a ratio by taking a firm's book value of total assets, subtracting its book value of equity, and adding on its market value of equity before dividing by its total assets. In this way, Tobin's Q displays a firm's relative valuation to its intrinsic value, where we assume that the book value and market value of a firm's liabilities are the same. Thus, a firm with Tobin's Q less than one can be interpreted as being undervalued and having a replacement cost of its assets greater than the value of its stocks. Likewise, a firm with a Tobin's Q greater than one can be interpreted as being overvalued and having a replacement cost of its assets lower than the value of its stocks. The required variables are easily accessible and included in the collected dataset for all observations. The natural logarithm of Tobin's Q is used throughout the paper to account for any skewness in the sample distribution.

3.3 Risk Exposures

3.3.1 Any Risk Exposure

Any risk exposure is a dummy variable set to 1 if a firm faces any of the aforementioned risk exposures; otherwise, it is set to 0. Like other risk exposure variables introduced in this section, this variable will be the criteria for sub-setting the dataset for each regression model and the associated question of interest on the risk-derivative usage relationship.

3.3.2 Floating Interest Rate Exposure

Floating interest rate exposure is a dummy variable set to 1 if a firm holds any outstanding debt susceptible to interest rate fluctuations; otherwise, it is set to 0.

3.3.3 Foreign Exchange Exposure

FX risk can broadly be divided into three types: transaction risk, economic risk, and translation risk. Of interest are only transaction and economic risks, as these affect the cash flows related to operations and financing for a firm. In contrast, translation risk is only relevant for reporting purposes. Numbers associated with translation gain or loss from annual reports are therefore excluded.

FX exposure is a dummy variable set to 1 if a firm has operational or financial accounts affected by foreign currencies; otherwise, it is set to 0. This variable is linked to the Bloomberg Terminal continuous variable 'Net FX Gain', an incomplete variable that must be hand-collected to include all observations. As 'Net FX Gain' includes differing accounts, depending on the firm and accounting standard applied, its values are unreliable and inconsistent for comparison among firms. Some firms are not even reporting 'Net FX Gain', even though they explicitly state they are affected by FX exposure, so they will still have an FX exposure dummy equal to 1 while having their net FX account equal to 0.

To be more precise about what type of FX exposure a firm has, additional time was spent in hand-collecting whether or not a firm had FX sales or receivables, FX debt, or FX deposits. FX sales or receivables is a dummy for whether or not a firm makes sales in foreign currencies or is selling its products or services to accumulate accounts receivable in foreign currencies. FX debt is a dummy for whether or not a firm has debt in foreign currency, such that the funds are exposed to FX rates when interest or principal payments are due. Lastly, FX deposits is a dummy for whether or not a firm has funds in foreign accounts, such that the deposits are affected by exchange rate fluctuations.

Additionally, a firm has foreign currency exposure only when its functioning currency differs from any other currencies in an account, not solely if it is in NOK. Should a firm have another reporting or presentation currency, despite not being its functional currency and having no foreign currency accounts, it is not regarded as exhibiting FX exposure.

3.3.4 Commodity Exposure

When considering commodity price exposure, the interest lies in commodities used as raw materials in production processes or operations or if a firm is producing and selling the commodity in the markets. It should thus be relevant for a firm's cash flow and contribute to operational profits, not for investment or speculation purposes, and only then is the commodity exposure dummy set to 1. Additionally, commodities of interest should be commonly available and recognized for trade to make the study more defined. As firms can arrange any deal forward as they see fit, given another counterparty to accept the bet, the commodity possibilities are here delimited to get an exact definition of exposure. Such commodities could be energy commodities, like crude oil and natural gas, or industrial commodities, like copper, aluminum, and steel. Another relevant example is the use of bunker fuel for vessels. A full list of commodities considered can be found in Appendix A2.

Suppose a firm does not specify its usage and type of raw materials other than 'raw materials', which cannot be implied by the general business, sector, or other information from the annual reports. In that case, a firm is not considered exposed to commodities. This is again to be specific within the defined list of commodities and exclude firms that might subcontract the production abroad or to other manufacturing companies.

3.4 Independent Variables

3.4.1 Derivative Usage

Derivative usage is a dummy variable set to 1 if a firm uses any derivatives for hedging purposes; otherwise, it is set to 0. While total notional derivative amount, or total derivative gain/loss, could provide better insights into the derivative impact on valuation, such measurements are difficult to obtain due to inconsistency and lack of reporting of the firms. The dummy variable will thus only provide an average change between users and non-users. However, anticipation is still a positive relationship between derivative usage and firm value.

3.4.2 Interest Rate Derivatives

Interest rate derivative usage is a dummy for whether or not a firm uses interest rate derivatives to hedge its floating interest rate exposure. In addition, dummy variables on the usage of interest rate swaps, forward rate agreements, interest options, and interest rate caps are collected. Due to the lack of data, continuous variables of hedging ratios or notional amounts are not collected.

3.4.3 Foreign Exchange Derivatives

FX derivative usage is a dummy for whether or not a firm use FX derivatives to hedge its FX exposure. In addition, dummy variables on the usage of currency forwards, currency futures, currency swaps, currency options, or currency interest swaps are collected. Due to the lack of data, continuous variables of hedging ratios or notional amounts are not collected.

3.4.4 Commodity Derivatives

Commodity derivative usage is a dummy for whether or not a firm generally uses derivatives to hedge its commodity exposure. In addition, dummy variables on the usage of commodity forwards, commodity options, or commodity swaps are collected. For commodities, data on net commodity derivative gain is also acquired for each relevant firm, which is prevalent in the annual reports.

3.5 Control Variables

As suggested by other papers (e.g. Allayannis & Weston, 2001; Kim et al., 2017; Santos et al., 2017), we use different control variables that might affect firm value to isolate the derivatives' effect better.

3.5.1 Return on Assets

For a measure of profitability, the return on assets (ROA) is employed, as it is likely that more profitable firms will have a higher market valuation, which is also argued by Allayanis & Weston (2001) and Belghitar et al. (2013). More profitable firms might also be more likely to afford hedging in the first place than less profitable ones. If a user of derivatives is more profitable, it should thus have a higher firm valuation. ROA is the ratio of net income to book value of total assets, and the expectation is that ROA will have a positive coefficient and contribution to Tobin's Q.

3.5.2 Leverage

Capital structure is one of the real market imperfections that might affect firm value due to the tax benefits of debt, as originally argued by Modigliani & Miller (1958). While a foundational bedrock and arguably a potential reason for firms to perform risk management in the first place, studies by Magee (2008) and Belghitar et al. (2013) suggest a negative correlation between leverage and firm value. Leverage is considered the ratio of the book value of total liabilities to the book value of total assets with the predicted effect on Tobin's Q being uncertain.

3.5.3 Current Ratio

A firm's ability to meet its short-term liabilities is the current ratio, which is the book value of total current assets to the book value of total current liabilities. A lower current ratio should initially be recognized as a solvency problem and possibly be punished with a lower market valuation. While Farhan et al. (2019) found positive and significant effects on Tobin's Q, a study by Husna & Satria (2019) found insignificant effects. We still expect the current ratio to contribute positively to Tobin's Q.

3.5.4 Liquidity

While the current ratio includes all short-term assets, the effect of excess free cash flow, as hypothesized by Jensen (1986), is that of being invested in projects that generate negative net present value. Though Hagelin and Pramborg (2004) and Bartram et al. (2011) report similar evidence, Allayannis et al. (2012) and Campa & Kedia (2002) find opposing evidence. Therefore, the effect of cash alone is included, and liquidity is constructed as the ratio of the book value of cash and cash equivalents to the book value of total current liabilities. The predicted effect is ambiguous.

3.5.5 Tangibility

Arilyn (2020) argued that firms with more tangible assets have better prerequisites for external financing and less financial distress due to broader pledging of collateral. This could also result in higher leverage levels, both positively considered by investors and higher firm valuation. Tangibility is thus included as the ratio of net fixed assets book value to total assets, and it is expected to contribute positively to Tobin's Q.

3.5.6 Firm Size

An initial assumption is that the bigger the firm, the higher its value due to economies of scale. However, while Allayannis & Weston (2001), Belghitar et al. (2013), and Chen & King (2014) suggest there is a negative correlation between firm size and firm value, Magee (2008) finds opposing results. While the final effect on Tobin's Q is uncertain, firm size is the natural logarithm of the book value of total assets, similar to Kim et al. (2017).

3.5.7 Industry

There might be different relative valuations of firms between industries due to macroeconomic cycles or other industry-specific factors. To account for this, an industry factor dummy is assigned to each firm, with the industry labels as Euronext specifies them. The impact might vary significantly depending on the industry in question.

3.6 Descriptive Statistics

Summary statistics on using any derivative by the sample firms are reported in Table 3.1. Across all firms, approximately 59.7 percent of the observations use at least one type of financial derivative. There is also a significant spread of usage between each industry, with the Health Care industry being the lowest and Telecommunications being the highest. This view is, however, skewed due to the existence of just two unique firms in the Telecommunications industry. Almost every firm is at some point in time exposed to one of the aforementioned risk exposures, as can be seen in the last column, giving rise to the incentive of using at least one type of derivative to hedge the exposure.

Table 3.1: Industry Breakdown of Derivative Usage & Risk Exposure

The table summarizes unique firms, total observations, derivative usage, and risk exposures in each industry. Derivative usage ratio is the proportion of observations with derivative usage, and any risk exposure ratio represents the proportion of observations with any risk exposure.

Industry	Unique Firms	Observations	Derivative Usage		Any Risk Exposure	
	Number	Number	Number	%	Number	%
Basic Materials	9	79	63	79.7	79	100
Consumer Discretionary	15	142	94	66.2	141	99.3
Consumer Staples	13	136	111	81.6	136	100
Energy	42	494	303	61.3	494	100
Health Care	14	127	17	13.4	125	98.4
Industrials	55	554	382	69.0	552	99.6
Real Estate	6	66	38	57.6	66	100
Technology	24	206	61	29.6	191	92.7
Telecommunications	2	24	21	87.5	24	100
Utilities	5	11	8	72.7	11	100
Total	185	1839	1098	59.7	1819	98.9

Table 3.2: Industry Breakdown of Derivative Usage & Risk Exposure by Risk

This expanded table provides detailed information on each risk exposure, including the count of exposures, derivative user, and the hedger to exposure ratio.

Industry	Floating Interest Rate			Foreign Exchange			Commodity		
	Exposure	Derivatives	%	Exposure	Derivatives	%	Exposure	Derivatives	%
Basic Materials	72	31	43.1	79	55	69.6	79	55	69.6
Consumer Discretionary	109	64	58.7	124	68	54.8	45	30	66.7
Consumer Staples	132	86	65.2	136	109	80.1	114	78	68.4
Energy	400	260	65.0	493	226	45.8	452	76	16.9
Health Care	55	0	0.0	119	17	14.3	0	0	-
Industrials	490	281	57.3	539	298	55.3	432	90	20.8
Real Estate	53	35	66.0	52	15	28.8	0	0	-
Technology	110	25	22.7	191	61	31.9	15	0	0.0
Telecommunications	18	15	83.3	21	21	87.5	0	0	-
Utilities	7	3	42.9	10	3	30.0	11	4	36.4
Total	1446	800	55.3	1767	873	49.4	1148	333	29.0

Digging deeper into what type of risk exposure a firm faces and whether the firm uses derivatives to hedge this risk, Table 3.2 provides better insights. Interestingly, 1767 out of 1839 observations face foreign exchange exposure, giving rise to the introductory hypothesis of Norwegian firms depending on international trade. This exposure is hedged by almost 50 percent of exposed observations. Moreover, while 1446 observations are exposed to floating interest rates, roughly 55 percent of exposed observations hedge this risk. Therefore, floating interest rate risk is preferred to hedge over foreign exchange risk. With 1148 sample observations exposed to commodity risk, only about 29 percent of exposed observations hedge this risk. Differences across industries are once again observable.

Table 3.3: Derivative Instruments Usage & Percentage by Risk Exposure

This expanded table provides detailed information on each risk exposure, including the count of exposures, derivative instruments user, and the hedger to exposure ratio.

Industry	Floating Interest Rate			Foreign Exchange			Commodity		
	Obs.	Derivatives	%	Obs.	Derivatives	%	Obs.	Derivatives	%
Forward	1446	55	3.8	1767	805	45.6	1148	203	17.7
Option	1446	37	2.6	1767	108	6.1	1148	91	7.9
Swap	1446	788	54.5	1767	288	16.3	1148	121	10.5
Cap	1446	22	1.5	1767	-	-	1148	-	-

Table 3.3 presents the distribution of derivative instruments usage when firms face corresponding risk exposures. Interestingly, out of 1,446 observations, 788 observations (approximately 55 percent) utilize interest rate swaps when facing floating interest rate exposure, making it the most popular instrument for hedging this risk. Additionally, among the 1767 observations exposed to floating interest rates, approximately 46 percent hedge this risk using currency forwards, the most popular instrument in this category. For the 1148 sample observations exposed to commodity risk, only about 18 percent hedge this risk using commodity forwards, the most popular instrument in this category. Notably, there are observable differences across industries.

Table 3.4: Any Derivative Usage for Different Time Intervals

This table displays the number of uniquely listed firms on the main Norwegian stock markets, along with the total observations and total amount of derivative users, subdivided into 3-year intervals over the collected sample.

Period	Unique Firms	Observations	Derivative Usage	
	Number	Number	Number	%
2007-2009	90	264	169	64.0
2010-2012	102	300	183	61.0
2013-2015	127	350	217	62.0
2016-2018	144	410	238	58.0
2019-2021	185	515	291	56.5

Table 3.4 exhibits the trend of general derivative usage over time. While there seems to be a downward-sloping trend of derivative usage, this might partially be explained by more firms being listed on the stock markets, as seen in the second column. These new listings are often younger and smaller firms, and they might not as often use derivatives, as Bartram et al. (2011) argued. The time intervals were chosen to consider the mid-financial crisis, the aftermaths of the financial crisis, a couple of stable periods in-between crises, and finally the Covid-19 pandemic.

Table 3.5: Derivative Usage by Risk Exposure for Different Time Intervals

This expanded table provides detailed information on each risk exposure, including the count of exposures, derivative user, and the hedger to exposure ratio.

Period	Floating Interest Rate			Foreign Exchange			Commodity		
	Exposure	Derivatives	%	Exposure	Derivatives	%	Exposure	Derivatives	%
2007-2009	213	115	54.0	252	147	58.3	177	49	27.7
2010-2012	234	137	58.5	283	153	54.1	198	63	31.8
2013-2015	271	161	59.4	333	174	52.3	221	64	29.0
2016-2018	308	175	56.8	396	184	46.5	245	69	28.2
2019-2021	420	212	50.5	503	215	42.7	307	88	28.7

Looking into each risk exposure and derivative usage, Table 3.5 displays the breakdown across the different time intervals. After the financial crisis, interest rates were plummeting which might partially explain the increased use of interest rate derivatives. Interest rates were also starting to climb again at the end of 2017 before diving into the pandemic at the start of 2020. The increased uncertainty might therefore explain the further decline of interest rate derivatives. Foreign exchange does not exhibit the same movement and is only decreasing, while commodity derivatives somewhat follow the same pattern right after the financial crisis.

Lastly, an interesting question is how firm characteristics vary between derivative users and non-users. Table 3.6 looks at the difference between Tobin's Q and the control variables for the two groups.

Table 3.6: Difference in Variables between Derivative Users and Non-users

This table displays the mean and standard deviation of Tobin's Q and each of the control variables, when accounting for whether a firm uses derivatives or not in general. The two last columns display the difference in means between derivative users and non-users and the p-values when testing for the significance in differing means.

Variable	Users		Non-users		Difference in Means	p-value
	Mean	Std.Dev.	Mean	Std.Dev.		
Tobin's Q	0.190	0.499	0.571	0.968	-0.381	0.000***
Return on Assets	0.013	0.159	-0.262	1.817	0.275	0.000***
Leverage	0.597	0.196	0.417	0.398	0.180	0.000***
Current Ratio	1.874	4.117	8.959	51.075	-7.085	0.000***
Liquidity	0.750	2.284	6.999	49.315	-6.249	0.001***
Tangibility	0.430	0.291	0.218	0.284	0.212	0.000***
Size	8.935	1.731	6.341	1.585	2.594	0.000***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Interestingly, every difference between users and non-users of derivatives is significant at the 99 percent level. Moreover, Tobin's Q is significantly lower for derivative users, while ROA is higher. Leverage is also higher for hedgers, while the current ratio is much lower. This might make sense, as higher leverage means more short-term liabilities. On that note, liquidity is also much lower for hedgers with an average ratio of less than one. Hedgers also have more tangible assets and are generally much bigger firms. All this might point to the fact that hedgers are large, mature value companies, while non-hedgers are smaller growth companies.

Additional graphs and plots revealing dataset relationships can be found in Appendix A3. These reveal how general derivative usage and derivative type usage change over the time period, and what type of derivative instrument is most favored among firms. They also reveal that derivative usage is more common for larger than smaller firms. While the usage ratio varies between the two groups, the within-group ratios for instrument selection and risk hedging exhibit a significant similarity.

4 Methodology

4.1 Benchmark Regression

According to previous assumptions, to study the impact of derivative usage on corporate performance, this paper designs the following model:

$$Ln(TQ)_{i,t} = \beta_0 + \beta_1 DER_{i,t} + \beta' X_{i,t} + \epsilon_{i,t} \tag{4.1}$$

Where the notations represent:

- $Ln(TQ)_{i,t}$: Equals the natural logarithm of Tobin's Q for firm i in year t, where the book value of total assets minus book value of equity plus the market value of equity in the numerator and book value of assets in the denominator measures Tobin's Q. All book values are obtained from Bloomberg, while the market value of equity is calculated by multiplying the total outstanding shares obtained from Bloomberg with the stock price on the last trading day of the year from Euronext. We also adjust the market capitalization for firms that issue shares in diverse classes by using the data from Compustat.
- $DER_{i,t}$: Equals one if the firm i in year t reports the use of specific derivative contracts for hedging purposes in its annual report, zero otherwise. The derivatives include interest rate derivatives, currency derivatives, and commodity derivatives.
- $X_{i,t}$[2]: Equals a vector of firm-specific control variables for firm i in year t, including firms' leverage ($LEV_{i,t}$), liquidity ratio ($LIQ_{i,t}$), current ratio ($CURR_{i,t}$), return on assets ($ROA_{i,t}$), natural logarithm of assets ($lSize_{i,t}$) and fixed asset ratio ($Tangibility_{i,t}$).

In our initial tests, we decide to apply the above Ordinary Least Squares (OLS) estimation on the subsample of firms with the appropriate match between derivative usage and risk exposure. Therefore, the estimation in our study is conditional. Furthermore, we adopt fixed effects for firms and years to control for unobserved time-varying effects and measure within-firm differences in the effect of derivative usage. We choose fixed effects

[2]Variable 'Industry' is excluded due to issues of multicollinearity

over random effects due to the Hausman test rejecting all null hypotheses of the random effect estimator being the most efficient, and thus that the fixed effect estimator is at least as consistent and preferred. Hence, the transformation of our initial model will be:

$$Ln(TQ)_{i,t}|e_{i,t} = \beta_0 + \beta_1 DER_{i,t} + \beta' X_{i,t} + \gamma_t + \phi_i + \epsilon_{i,t} \tag{4.2}$$

Here we define $e_{i,t}$ as the condition representing the type of exposure the firm i in year t is confronted with, and it should correspond to the risk mainly hedged by the appropriate derivatives. The risks are namely floating interest rate exposure, currency exchange exposure, and commodity price exposure. Also, we have introduced γ_t, the time fixed effects, and ϕ_i, the firm fixed effects, to the model above. Therefore, the complete OLS model should be in the following format:

$$\begin{aligned} Ln(TQ)_{i,t}|e_{i,t} = \beta_0 + \beta_1 DER_{i,t} + \beta_2 LIQ_{i,t} + \beta_3 CURR_{i,t} + \beta_4 LEV_{i,t} + \\ \beta_5 ROA_{i,t} + \beta_6 lSize_{i,t} + \beta_7 Tangibility_{i,t} + \gamma_t + \phi_i + \epsilon_{i,t} \end{aligned} \tag{4.3}$$

To reaffirm the calculation and sources of control variables $X_{i,t}$, we have:

- $LIQ_{i,t}$: Equals firm i's total cash & cash equivalent over current liabilities in year t.
- $CURR_{i,t}$: Equals firm i's current assets divided by current liabilities in year t.
- $LEV_{i,t}$: Equals firm i's total liabilities divided by total assets in year t.
- $ROA_{i,t}$: Equals firm i's net income divided by total assets in year t.
- $lSize_{i,t}$: Equals the natural logarithm of firm i's total assets in year t.
- $Tangibility_{i,t}$: Equals firm i's net fixed assets divided by total assets in year t.

4.2 Quantile Regression

Considering that the distribution of the dependent variable Ln(Tobin's Q) might not be normally distributed, which is one of the conditions required by the OLS model, we decide to use a more flexible framework to explore characteristics of different quantiles rather than just the mean of the response, with quantile regressions. Uribe & Guillen (2020) state that quantile regression models could help understand the potential influences of extreme responses, and they also present the framework that helps us explore the value of the conditional distribution of the response at the 5th or 95th quantile levels.

When we look into the graph of the quantile distribution of the dependent variable Ln(Tobin's Q) in Figure 4.1, we find that the distribution of the dependent variable has a fat right tail, meaning that it does not sufficiently satisfy the assumption of the OLS model. The potential issue is that the regression estimator is not consistent across the quantiles:

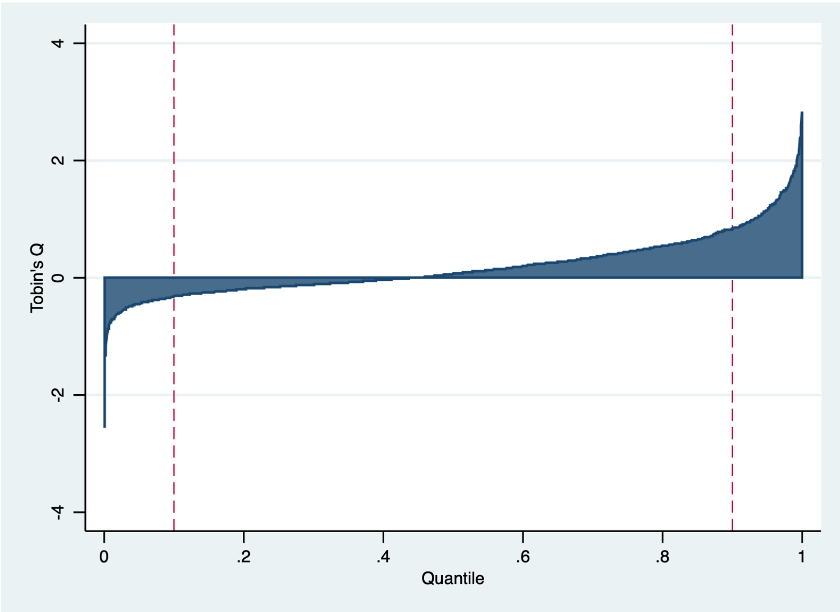

Figure 4.1: Quantile Distribution of Ln(Tobin's Q)

This figure shows the distribution characteristics of the dependent variable Ln(Tobin's Q) in the quantile range [0,1]

Therefore, instead of focusing exclusively on changes in the means, and according to the aforementioned framework, we define our Quantile Regression (QR) model to explore changes in multiple points of the distributions as follows:

$$Q_\theta[Ln(TQ)_{i,t}|e_{i,t}] = \beta_{\theta,0} + \beta_{\theta,1}DER_{i,t} + \beta_{\theta,2}LIQ_{i,t} + \beta_{\theta,3}CURR_{i,t} + \beta_{\theta,4}LEV_{i,t} + \beta_{\theta,5}ROA_{i,t} + \beta_{\theta,6}lSize_{i,t} + \beta_{\theta,7}Tangibility_{i,t} + \gamma_t + \phi_i + \epsilon_{i,t} \quad (4.4)$$

The coefficients of seven distinct θth quantiles - 5th, 10th, 25th, 50th, 75th, 90th, and 95th - are estimated utilizing identical explanatory factors. We chose the quantile regression estimator proposed by Machado & Silva (2019), which is a generalized method of moments (GMM) estimator, given its broader applicability in various models, including non-linear models and models with endogenous variables. The estimator does not impose a uniform fixed effects impact across all quantiles, while Koenker's (2004) estimator enforces this restriction. Efron's (1979), within cluster bootstrap method, which is a process that generates new samples to replace original data for estimating the covariance matrix of the quantile regression parameter vector, is employed for standard error estimation.

The quantile regression methodology yields a sequence of quantile coefficients for each sample quantile. It allows us to test the varying responses of Tobin's Q to alterations in the regressors, contingent on whether a firm is located in the distribution's left tail (low Tobin's Q) or right tail (high Tobin's Q).

4.3 Difference-in-Difference: Event Study

While the OLS and quantile regressions delineated earlier illuminate correlations, they do not necessarily denote causation and could be subject to endogeneity issues. In our case, it would be impossible to control the whole system randomly and implement a randomized experiment, so we decided to use another tool for causal inference.

One common approach to causality estimation is the Difference-in-Difference (DiD) model, which is proficient in addressing endogeneity. Here, a firm belongs to a treatment group if it uses a derivative, while the control group consists of firms that do not use derivatives. Then, we designate the period before and after a derivative user started to use derivatives as the pre-and post-treatment period. We then wish to see how implementing derivatives affected firm value over a period of time. However, the standard DiD model's limitation is its binary nature - it only considers two groups over two time periods, thereby leading to its categorization as a 2 × 2 DiD model. Our model is as follows:

$$y_{g,t} = \gamma_g + \phi_t + \delta D_{g,t} + \epsilon_{g,t} \tag{4.5}$$

Here, the parameters are denoted as the following:

- y_{gt} : Outcome y for group g over period t.

- γ_g : Fixed effects for group g
- ϕ_t : Fixed effects for period t
- D_{gt} : Binary treatment variable which turns from 0 to 1 if the group g over period t is treated and is in a post-treatment period.

This model beneficially allows us to estimate the dynamic effects of policies at distinct periods post-treatment by imposing a comparable treatment period for each group. Given that policies are implemented over a long time horizon at the aggregate level, the generalized 2×2 DiD estimator can handle periods of treatment withdrawal and multiple treatment paths. To apply an event-study specification, we reframe the 2×2 DiD model into the following form:

$$Ln(TQ)_{g,t} = \gamma_g + \phi_t + \Sigma_{T=T_l-\tau_g}^{T_h-\tau_g} \delta_T D_{g,T} + \beta' X_{g,t} + \epsilon_{g,t} \tag{4.6}$$

Here we replace outcome y with $Ln(TQ)_{g,t}$ to cater to our study. Meanwhile, we define τ_g as the closest and first treatment time for group g. T_l and T_h are the lowest and highest number of leads and lags surrounding the treatment period. We also impose the normalization $\delta_{-1} = 0$, the coefficient for the last period before the treatment. This adjustment intends to avoid perfect multicollinearity. The adjusted $D_{g,T}$ is still a dummy variable, equaling 1 if $T - \tau_g$ is not negative; 0 otherwise (and 0 for all never-treated groups). Also, we add $X_{g,t}$, which denotes a vector of firm-specific covariates at group g in year t, that shares the same control variables as mentioned above. In addition, estimation is generally performed with standard errors clustered at the group level. Therefore, our DiD event studies can be explicitly expanded into:

$$Ln(TQ)_{g,t} = \gamma_g + \phi_t + \Sigma_{T=T_l-\tau_g}^{-2} \delta_T \times D_{g,T} + \Sigma_{T=0}^{T_h-\tau_g} \delta_T \times D_{g,T} + \beta' X_{g,t} + \epsilon_{g,t} \tag{4.7}$$

Although two-way fixed effects (TWFE), by controlling for time effects and group effects, are commonly used in DiD models, it has been shown that TWFE does not work for the variant with rollout design. This is because fixed effects only allow within variation, while there is no within variation between never-treated and already-treated groups. So far, several new estimators have proposed to deal with rollout designs properly. In our case, we mainly use the estimator Sun & Abraham (2020) provided. This method involves estimating treated cohort time to treatment dummies, which are then aggregated to calculate the average treatment effect for the treated (ATT) in each period or the entire post-treatment period. We compare these results using the tools that Gardner (2022) suggested, which instead implement two-stage difference-in-differences to deal with the TWFE problem.

The parallel trends assumption, crucial for the difference-in-differences model, suggests that the treated and control groups would follow the same trend without treatment. We will check this by plotting their trends over time. If the gap between the groups remains constant until treatment, we infer the treatment causes the changes. However, this is a suggestive check and not definitive proof, as the parallel trends assumption is untestable. Moreover, we also conduct a placebo test where we exclude all data from the periods when the actual treatment is implemented. Instead, we select different periods and assume that the treatment was applied during those times for comparison. This allows us to evaluate the potential impact of the treatment in a simulated setting.

5 Analysis

We present the empirical results for the fixed effect OLS and quantile regression models for diverse derivatives. However, it is important to note that we do not provide the R-squared results for the quantile regressions, as it is not meaningful in this context. This is because R-squared measures the goodness of fit based on the mean response. In contrast, quantile regressions focus on estimating conditional quantiles that represent different parts of the response distribution. Next, we present the main results by evaluating the treatment effects of derivative usage using the dynamic difference-in-difference approach.

5.1 Baseline and Quantile Regression

5.1.1 Derivative Usage

In Table 5.1, we present the fixed effect OLS and quantile regression estimates by analyzing derivative usage for firms with the interest rate, foreign exchange, and commodity price exposures. In other words, for the selected firms with exposure to any risk exposure. All quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the OLS results, we conclude that derivative usage has a positive but insignificant relationship with firm value, and this relationship is not significant at any quantiles either. Meanwhile, derivatives used by firms with high values at the 90th and 95th quantiles are insignificantly negatively related to firm value. The quantile regression results demonstrate that the coefficients of derivative usage vary significantly across all quantiles, ranging from 0.0482 for a firm in the 5th conditional quantile to -0.0033 for a firm in the 95th conditional quantile. Interpreting these coefficients in the context of quantile regressions allows us to compare how changes in derivative usage translate into changes in Ln(Tobin's Q) when firm value is relatively high (in high quantiles) or relatively low (in low quantiles). For example, a switch from zero to one in derivative usage is associated with a 4.82 percent increase in firm value when the firm's value is relatively low at the 5th quantile. Conversely, a switch from zero to one in derivative usage is associated with a 1.11 percent decrease in firm value when the firm's value is relatively high at the 95th quantile.

Table 5.1: Baseline and Quantile Regressions: Derivatives Usage

This table shows the impact of General Derivative Usage on firm value for the sample with bearing floating interest rate exposure, currency exposure and commodity price exposure. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 183 unique firms, listed in Oslo Stock Exchange, and comprises 1,819 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Dev	0.0211	0.0482	0.0432	0.0349	0.0223	0.0076	-0.0033	-0.0111
	(0.29)	(0.61)	(0.56)	(0.46)	(0.29)	(0.09)	(-0.03)	(-0.11)
Liq	0.0031	0.0107	0.0093	0.0070	0.0034	-0.0007	-0.0038	-0.0060
	(0.46)	(0.74)	(0.68)	(0.56)	(0.31)	(-0.07)	(-0.35)	(-0.53)
Curr	-0.0044	-0.0124	-0.0110	-0.0085	-0.0047	-0.0004	0.0028	0.0051
	(-0.63)	(-1.32)	(-1.24)	(-1.06)	(-0.64)	(-0.05)	(0.32)	(0.54)
Lev	0.1503	0.1475	0.1480	0.1489	0.1502	0.1517	0.1528	0.1536
	(1.23)	(0.90)	(0.94)	(0.98)	(0.98)	(0.91)	(0.82)	(0.77)
ROA	**-0.0429*****	-0.0502	-0.0489	-0.0466	-0.0432	-0.0392	-0.0362	-0.0341
	(-6.39)	(-0.65)	(-0.68)	(-0.72)	(-0.76)	(-0.71)	(-0.60)	(-0.52)
lSize	**-0.1409*****	**-0.0818****	**-0.0926****	**-0.1108*****	**-0.1383*****	**-0.1705*****	**-0.1943*****	**-0.2112*****
	(-3.97)	(-2.02)	(-2.44)	(-3.12)	(-4.08)	(-4.84)	(-4.95)	(-4.87)
Tangibility	-0.0574	-0.1147	-0.1042	-0.0866	-0.0599	-0.0287	-0.0057	0.0107
	(-0.35)	(-0.68)	(-0.64)	(-0.54)	(-0.34)	(-0.14)	(-0.02)	(0.04)
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,819	1,819	1,819	1,819	1,819	1,819	1,819	1,819
R^2	0.20							

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Upon examining the coefficients of the control variables, we observe a negative and significant association at the 1 percent level between firm size (log of total assets) and firm value. Also, the ROA demonstrates a negative relationship, contrary to the expected positive relationship between profitability and firm value. Notably, this association is primarily observed in the OLS estimation, with no significant effects detected across any quantiles.

Although **hypothesis 1a** is expecting a positive association between derivative usage and firm value when exposed to relevant risks, it cannot be confirmed due to the absence of a significant average relationship. However, the negative associations in the high-level quantile regressions are still worth noting. Additionally, we find that the relationships between derivative usage and firm value vary across quantiles. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not statistically significant.

5.1.2 Interest Rate Derivative

In Table 5.2, we present the fixed effect OLS and quantile regression estimates by analyzing the use of interest rate derivatives for firms with interest rate exposure only. In other words, for the selected firms with exposure to floating interest rates. All quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the OLS results, we can conclude that interest rate derivatives have a positive but insignificant relationship with firm value. However, this relationship is significant in some of the quantiles. The quantiles below the median display are positively strong relationships. Additionally, the quantile regressions reveal that interest rate derivative usage coefficients vary significantly across quantiles, ranging from 0.0975 for a firm in the 5th conditional quantile to 0.0909 for a firm in the 95th conditional quantile. Interpreting these coefficients, a switch from zero to one in interest rate derivative usage is associated with a 9.75 percent increase in firm value, or Tobin's Q, when the firm's value is at the 5th quantile (relatively low), and a 9.09 percent increase when the firm's value is at the 95th quantile (relatively high).

Table 5.2: Baseline and Quantile Regressions: Interest Rate Derivatives

This table shows the impact of Interest Rate Derivative Usage on firm value for the sample with liabilities bearing floating interest rate. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Interest Rate Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 164 unique firms, listed in Oslo Stock Exchange, and comprises 1,446 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Interest_Dev	0.0945	**0.0975****	**0.0970****	**0.0961****	**0.0947****	0.0930	0.0916	0.0909
	(1.54)	(2.09)	(2.16)	(2.18)	(1.97)	(1.55)	(1.27)	(1.14)
Liq	0.0123	-0.0016	0.0007	0.0049	0.0112	0.0194	0.0256	0.0292
	(1.04)	(-0.06)	(0.03)	(0.22)	(0.50)	(0.68)	(0.72)	(0.73)
Curr	-0.0066	0.0019	0.0006	-0.0020	-0.0059	-0.0109	-0.0146	-0.0169
	(-1.41)	(0.19)	(0.06)	(-0.24)	(-0.66)	(-0.86)	(-0.88)	(-0.89)
Lev	**0.4485*****	**0.4846*****	**0.4788*****	**0.4680*****	**0.4515*****	**0.4302*****	**0.4142****	**0.4048****
	(4.23)	(4.05)	(4.13)	(4.12)	(3.77)	(3.05)	(2.53)	(2.27)
ROA	0.0655	0.0341	0.0391	0.0486	0.0630	0.0816	0.0955	0.1037
	(0.85)	(0.32)	(0.39)	(0.52)	(0.69)	(0.78)	(0.77)	(0.76)
lSize	-0.0504	-0.0174	-0.0227	-0.0326	**-0.0477***	**-0.0672***	**-0.0817***	**-0.0903***
	(-1.58)	(-0.62)	(-0.88)	(-1.36)	(-1.83)	(-1.93)	(-1.83)	(-1.77)
Tangibility	-0.1250	-0.0029	-0.0225	-0.0592	-0.1151	-0.1871	-0.2410	-0.2730
	(-0.89)	(-0.02)	(-0.17)	(-0.46)	(-0.87)	(-1.18)	(-1.30)	(-1.35)
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,446	1,446	1,446	1,446	1,446	1,446	1,446	1,446
R^2	0.18							

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The quantile regression results differ from those obtained using the fixed effect OLS regression. Additionally, some control variables demonstrate the significance and exhibit the expected signs. By examining the effects of covariates, we observe a negative and significant association at the 10% level between firm size (log of total assets) and firm value. This association is particularly strong at high quantiles. In contrast, the ROA demonstrates a positive relationship with firm value at the average level, aligning with expectations that more profitable firms would have higher values.

Although not all OLS and quantile regressions present significant results, we can confirm from **hypothesis 1b** that interest rate derivative usage is positively associated with firm value when firms are exposed to floating interest rates, particularly when the value of a firm is below the median. Additionally, we find that the relationship between interest rate derivative usage and firm value varies across quantiles. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not always statistically significant.

5.1.3 Currency Derivative

In Table 5.3, we present the fixed effect OLS and quantile regression estimates by analyzing the use of currency derivatives for the firms that face currency exposure. In other words, for the selected firms exposed to floating foreign exchange risks. All the quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the OLS results, we can conclude that currency derivative usage has a positive but insignificant relationship with firm value, and this relationship is not significant for any quantiles either. Meanwhile, the quantile regressions reveal that the coefficient of currency derivative usage varies significantly across quantiles, ranging from 0.0164 for a firm in the 5th conditional quantile to 0.0682 for a firm in the 95th conditional quantile. Interpreting these coefficients for the quantile regressions, a switch from zero to one in currency derivative usage is associated with a 1.64 percent increase in firm value, or Tobin's Q, when the firm's value is at the 5th quantile (relatively low), and a 6.82 percent increase when the firm's value is at the 95th quantile (relatively high).

Table 5.3: Baseline and Quantile Regressions: Currency Derivatives

This table shows the impact of Currency Derivative Usage on firm value for the sample with sales and operations bearing voalitile foreign exchange rate. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Currency Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 181 unique firms, listed in Oslo Stock Exchange, and comprises 1,767 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Currency_Dev	0.0401	0.0164	0.0206	0.0279	0.0393	0.0519	0.0620	0.0682
	(0.60)	(0.26)	(0.35)	(0.47)	(0.59)	(0.62)	(0.61)	(0.60)
Liq	**0.0121*****	0.0157	0.0151	0.0139	0.0122*	0.0102*	0.0087	0.0077
	(2.94)	(1.31)	(1.37)	(1.48)	(1.70)	(1.86)	(1.58)	(1.26)
Curr	**-0.0135*****	**-0.0170****	**-0.0164****	**-0.0153****	**-0.0136*****	**-0.0117*****	**-0.0102****	**-0.0092***
	(-3.06)	(-1.96)	(-2.08)	(-2.27)	(-2.62)	(-2.79)	(-2.32)	(-1.88)
Lev	0.1298	0.1325	0.1321	0.1312	0.1299	0.1284	0.1273	0.1266
	(1.13)	(0.84)	(0.87)	(0.91)	(0.90)	(0.82)	(0.72)	(0.66)
ROA	**-0.0413*****	-0.0495	-0.0480	-0.0455	-0.0416	-0.0372	-0.0337	-0.0316
	(-6.09)	(-0.59)	(-0.61)	(-0.64)	(-0.65)	(-0.58)	(-0.47)	(-0.40)
lSize	**-0.1486*****	**-0.0850****	**-0.0963*****	**-0.1158*****	**-0.1465*****	**-0.1803*****	**-0.2075*****	**-0.2239*****
	(-4.22)	(-2.20)	(-2.59)	(-3.22)	(-4.02)	(-4.59)	(-4.79)	(-4.78)
Tangibility	-0.0876	-0.1373	-0.1284	-0.1132	-0.0892	-0.0627	-0.0415	-0.0286
	(-0.51)	(-0.83)	(-0.77)	(-0.66)	(-0.46)	(-0.27)	(-0.15)	(-0.10)
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,767	1,767	1,767	1,767	1,767	1,767	1,767	1,767
R^2	0.24							

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The quantile results differ from those obtained using the fixed effect OLS regression. Additionally, certain control variables demonstrate the significance and exhibit the expected signs. Upon examining the effects of covariates, we find a negative and significant association at the 1 percent level between firm size (log of total assets) and firm value. In contrast, the ROA demonstrates a negative relationship at the average level, contrary to the expectation that higher profitable firms would have a higher value. Notably, this association is primarily observed in the OLS estimation, with no significant effects detected across any quantile.

Although **hypothesis 1c** is expecting a positive association between currency derivative usage and firm value when exposed to floating foreign exchange rate risks, this cannot be confirmed due to the absence of a significant average relationship. Still, the relationships between derivative usage and firm value vary across quantiles. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not statistically significant.

5.1.4 Commodity Derivative

In Table 5.4, we present the fixed effect OLS and quantile regression estimates by analyzing the usage of commodity derivatives for the firms that face commodity price exposure. In other words, for the selected firms with exposure to floating commodity prices. All the quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the OLS results, we conclude that commodity derivatives have a positive but insignificant relationship with firm value. However, this relationship varies across quantiles. The quantiles below the median present positively strong relationships. Meanwhile, firms with high values at the 90th and 95th quantiles have negative coefficients for commodity derivative usage, though they are insignificant. The quantile regression results highlight the wide variation in these coefficients across quantiles, ranging from 0.1880 for the 5th conditional quantile to -0.0589 for the 95th conditional quantile. In terms of interpretation, switching from zero to one in commodity derivative usage is associated with an 18.8 percent increase in firm value, or Tobin's Q, when the firm's value is at the 5th quantile (relatively low), and a 5.89 percent decrease when the firm's value is at the 95th quantile (relatively high).

The quantile results differ from those obtained using the fixed effect OLS regression. Additionally, certain control variables demonstrate the significance and exhibit the expected signs. Based on the effects of covariates, we find that firm size (log of total assets) has a negative and significant association with firm value at the 10 percent level. In contrast, ROA exhibits a negative relationship at the average level, contrary to the expectation that more profitable firms would have a higher value. Notably, this association is primarily observed in the OLS estimation, with no significant relationship detected across quantiles. On the other hand, the leverage ratio demonstrates strong positive relationships at the mean and the quantiles below the median.

Although not all OLS or quantile regressions present significant results, we can confirm for **hypothesis 1d** that commodity derivative usage is positively associated with firm value when firms are exposed to floating commodity price risks, particularly when the firm's value is below the median. Additionally, we find that the relationship between commodity derivative usage and firm value varies across quantiles. This finding aligns with our expectation to conduct quantile analysis, even though not all relationships are statistically significant.

Table 5.4: Baseline and Quantile Regressions: Commodity Derivatives

This table shows the impact of Commodity Derivative Usage on firm value for the sample with sales bearing floating commodity price. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Commodity Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 111 unique firms, listed in Oslo Stock Exchange, and comprises 1,148 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Commodity_Dev	0.0741	**0.1880*****	**0.1665*****	**0.1346*****	0.0853	0.0170	-0.0270	-0.0589
	(1.22)	(3.20)	(3.10)	(2.66)	(1.47)	(0.21)	(-0.26)	(-0.48)
Liq	0.0023	0.0128	0.0109	0.0079	0.0033	-0.0030	-0.0071	-0.0100
	(0.29)	(0.53)	(0.49)	(0.41)	(0.22)	(-0.23)	(-0.51)	(-0.66)
Curr	-0.0036	-0.0143	-0.0123	-0.0093	-0.0047	0.0017	0.0058	0.0088
	(-0.44)	(-0.90)	(-0.84)	(-0.72)	(-0.43)	(0.16)	(0.50)	(0.68)
Lev	**0.3072***	**0.5572*****	**0.5102*****	**0.4400*****	**0.3318****	0.1819	0.0854	0.0154
	(1.92)	(3.06)	(2.92)	(2.67)	(2.05)	(1.06)	(0.45)	(0.07)
ROA	**-0.0449*****	-0.0527	-0.0512	-0.0490	-0.0457	-0.0410	-0.0380	-0.0358
	(-6.61)	(-0.47)	(-0.46)	(-0.44)	(-0.40)	(-0.33)	(-0.28)	(-0.25)
lSize	**-0.0833***	-0.0423	-0.0500	-0.0615	**-0.0792***	**-0.1038****	**-0.1196****	**-0.1311****
	(-1.97)	(-0.95)	(-1.16)	(-1.46)	(-1.84)	(-2.15)	(-2.20)	(-2.18)
Tangibility	-0.2302	-0.2952	-0.2830	-0.2647	-0.2366	-0.1976	-0.1725	-0.1543
	(-1.30)	(-1.58)	(-1.58)	(-1.54)	(-1.34)	(-0.97)	(-0.74)	(-0.60)
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,148	1,148	1,148	1,148	1,148	1,148	1,148	1,148
R^2	0.19							

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Instruments Heterogeneity Test

5.2.1 Derivative Instruments

In Table 5.5, we present the fixed effect OLS and quantile regression estimates by analyzing the usage of different derivative instruments for the firms with interest rate, foreign exchange, and commodity price exposures. In other words, for the selected firms with exposure to any risks. All quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the results obtained through the OLS regression, our findings indicate that options and caps (specifically interest rate caps) exhibit significant negative associations with firm value. Conversely, swaps display a significant positive relationship with firm value. However, the relationship between forwards and firm value is negative yet statistically insignificant. Moreover, our quantile regression analysis provides further insights. Specifically, we observe that the coefficients across all quantiles are insignificant and negative for forwards. Firms with values above the 50th quantile demonstrate a strong negative relationship for options. For caps, firms with values above the 25th quantile exhibit a noteworthy negative relationship. In contrast, firms with values below the 75th quantile exhibit a strong positive relationship for swaps.

Upon examining the coefficients of control variables, we observe a negative and significant association at the one percentage level between firm size (log of total assets) and firm value. Also, the ROA demonstrates a negative relationship, contrary to the expected positive relationship between profitability and firm value. Notably, this association is primarily observed in the OLS estimation, with no significant effects in any of the quantiles.

Although not all OLS or quantile regressions present significant results, we can confirm that option and cap derivatives negatively affect firm value. Swap derivatives positively associate firm value, and forward derivatives do not show any significant relationship. Additionally, we find that the relationships between different derivative instruments and firm value vary across quantiles. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not always statistically significant.

Table 5.5: Baseline and Quantile Regressions: Derivative Instruments

This table shows the impact of General Derivative Instruments Usage on firm value for the sample with bearing floating interest rate exposure, currency exposure and commodity price exposure. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 183 unique firms, listed in Oslo Stock Exchange, and comprises 1,819 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Forward	-0.0251	-0.0362	-0.0341	-0.0307	-0.0256	-0.0197	-0.0150	-0.0124
	(-0.38)	(-0.53)	(-0.52)	(-0.48)	(-0.37)	(-0.24)	(-0.16)	(-0.12)
Option	**-0.1440****	-0.0822	-0.0935	-0.1125	**-0.1414****	**-0.1746*****	**-0.2011****	**-0.2155****
	(-2.40)	(-0.75)	(-0.95)	(-1.36)	(-2.11)	(-2.59)	(-2.46)	(-2.30)
Swap	**0.1477****	**0.1946*****	**0.1860*****	**0.1715*****	**0.1496*****	**0.1244***	0.1043	0.0934
	(2.46)	(3.22)	(3.24)	(3.13)	(2.66)	(1.90)	(1.37)	(1.12)
Cap	**-0.2432*****	-0.0483	-0.0840	**-0.1442***	**-0.2352****	**-0.3397*****	**-0.4232*****	**-0.4686*****
	(-3.68)	(-0.59)	(-1.11)	(-1.87)	(-2.51)	(-2.64)	(-2.64)	(-2.61)
Liq	0.0030	0.0107	0.0093	0.0069	0.0033	-0.0008	-0.0040	-0.0058
	(0.45)	(0.74)	(0.69)	(0.56)	(0.30)	(-0.07)	(-0.38)	(-0.52)
Curr	-0.0043	-0.0123	-0.0109	-0.0084	-0.0046	-0.0003	0.0031	0.0050
	(-0.62)	(-1.33)	(-1.25)	(-1.06)	(-0.63)	(-0.04)	(0.36)	(0.53)
Lev	0.1466	0.1362	0.1381	0.1413	0.1462	0.1517	0.1562	0.1586
	(1.21)	(0.78)	(0.82)	(0.88)	(0.94)	(0.93)	(0.88)	(0.84)
ROA	**-0.0417*****	-0.0472	-0.0462	-0.0445	-0.0419	-0.0390	-0.0367	-0.0354
	(-6.11)	(-0.60)	(-0.62)	(-0.67)	(-0.73)	(-0.72)	(-0.63)	(-0.57)
lSize	**-0.1497*****	**-0.0950****	**-0.1050*****	**-0.1219*****	**-0.1475*****	**-0.1768*****	**-0.2003*****	**-0.2130*****
	(-4.20)	(-2.34)	(-2.76)	(-3.41)	(-4.36)	(-5.03)	(-5.15)	(-4.98)
Tangibility	-0.0972	-0.1659	-0.1534	-0.1321	-0.1000	-0.0632	-0.0338	-0.0178
	(-0.62)	(-0.99)	(-0.95)	(-0.84)	(-0.59)	(-0.31)	(-0.14)	(-0.07)
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,819	1,819	1,819	1,819	1,819	1,819	1,819	1,819
R^2	0.22							

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.2 Interest Rate Derivative Instruments

In Table 5.6, we present the fixed effect OLS and quantile regression estimates by analyzing the use of interest rate derivative instruments for the firms with interest rate exposure only. In other words, for the selected firms with exposure to floating interest rates. All quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the OLS results, our findings indicate that options and swaps demonstrate a significant positive relationship with firm value. In contrast, caps (primarily interest rate caps) exhibit a significant negative relationship with firm value. However, the relationship between forwards and firm value is negative yet statistically insignificant. Further analysis using quantile regressions reveals additional insights. For forwards, quantiles below the 50th exhibit insignificant negative coefficients, while quantiles above the 50th display insignificant positive coefficients. Regarding options, firms with values below the 50th quantile exhibit strong positive relationships, while those above the 50th quantile show insignificant negative coefficients. Firms with values below the 90th quantile display strong positive relationships for swaps. In contrast, firms with values above the 50th quantile exhibit strong negative relationships for caps.

The quantile regression results differ from those obtained using the fixed effect OLS regression. Additionally, some control variables demonstrate the significance and exhibit the expected signs. By examining the effects of covariates, we observe a negative and significant association at the 10 percent level between firm size (log of total assets) and firm value. This association is particularly strong at high quantiles. In contrast, the leverage ratio demonstrates a positive relationship with firm value on average and at all quantile levels, suggesting that more debted firms have a higher value.

Although not all OLS or quantile regressions present significant results, we can confirm that cap derivatives have a negative association with firm value, options, and swaps have a positive association with firm value, while forwards do not show any significant relationship. Additionally, we find that the relationship between interest rate derivative instrument usage and firm value varies across quantiles. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not always statistically significant.

Table 5.6: Baseline and Quantile Regressions: Interest Rate Derivative Instruments

This table shows the impact of Interest Rate Derivative Instruments Usage on firm value for the sample with liabilities bearing floating interest rate. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Interest Rate Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 164 unique firms, listed in Oslo Stock Exchange, and comprises 1,446 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Forward	-0.0062	-0.1151	-0.0983	-0.0642	-0.0148	0.0502	0.0969	0.1260
	(-0.04)	(-0.83)	(-0.74)	(-0.49)	(-0.09)	(0.24)	(0.37)	(0.42)
Option	**0.1097****	**0.3730*****	**0.3324*****	**0.2500*****	**0.1305*****	-0.0266	-0.1395	-0.2098
	(2.57)	(3.37)	(3.94)	(5.43)	(2.85)	(-0.21)	(-0.74)	(-0.94)
Swap	**0.1127****	**0.1129****	**0.1129****	**0.1128*****	**0.1127****	**0.1126****	**0.1125***	0.1124
	(2.04)	(2.40)	(2.50)	(2.60)	(2.46)	(2.04)	(1.70)	(1.54)
Cap	**-0.2302****	-0.0665	-0.0917	-0.1429	**-0.2172****	**-0.3148****	**-0.3850****	**-0.4287****
	(-2.59)	(-0.61)	(-0.89)	(-1.46)	(-2.12)	(-2.44)	(-2.45)	(-2.46)
Liq	0.0129	-0.0015	0.0007	0.0052	0.0117	0.0203	0.0264	0.0302
	(1.06)	(-0.05)	(0.03)	(0.23)	(0.49)	(0.67)	(0.69)	(0.70)
Curr	-0.0068	0.0018	0.0005	-0.0022	-0.0061	-0.0113	-0.0150	-0.0173
	(-1.43)	(0.17)	(0.05)	(-0.26)	(-0.66)	(-0.83)	(-0.84)	(-0.85)
Lev	**0.4625*****	**0.5203*****	**0.5114*****	**0.4933*****	**0.4671*****	**0.4326*****	**0.4078****	**0.3923****
	(4.50)	(3.82)	(3.89)	(3.91)	(3.68)	(3.05)	(2.55)	(2.28)
ROA	0.0720	0.0479	0.0516	0.0592	0.0701	0.0846	0.0949	0.1014
	(0.95)	(0.50)	(0.56)	(0.67)	(0.79)	(0.83)	(0.80)	(0.78)
Size	**-0.0554***	-0.0202	-0.0257	-0.0367	**-0.0527****	**-0.0737****	**-0.0888***	**-0.0982***
	(-1.76)	(-0.74)	(-1.02)	(-1.56)	(-2.02)	(-2.06)	(-1.91)	(-1.84)
Tangibility	-0.1420	-0.0504	-0.0645	-0.0932	-0.1347	-0.1894	-0.2286	-0.2531
	(-0.98)	(-0.36)	(-0.48)	(-0.72)	(-1.01)	(-1.22)	(-1.26)	(-1.27)
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,446	1,446	1,446	1,446	1,446	1,446	1,446	1,446
R^2	0.19							

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.3 Currency Derivative Instruments

In Table 5.7, we present the fixed effect OLS and quantile regression estimates by analyzing the use of currency derivative instruments for firms with currency exposure. In other words, for the selected firms exposed to floating foreign exchange risks. All the quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the OLS results, our findings indicate a significant positive relationship between swap derivatives and firm value. However, we do not find a statistically significant relationship between forward derivatives and firm value, nor between option derivatives and firm value. Furthermore, our analysis highlights that firms with values below the 50th quantile demonstrate strong positive relationships with swap derivatives.

The quantile regression results differ from those obtained using the fixed effect OLS regression. Additionally, certain control variables demonstrate the significance and exhibit the expected signs. Upon examining the effects of covariates, we find a negative and significant association at the one percent level between firm size (log of total assets) and firm value. In contrast, the ROA demonstrates a negative relationship at the average level, contrary to the expectation that higher profitable firms would have a higher value. Notably, this association is primarily observed in the OLS estimation, with no significant effects detected across quantiles.

Although not all OLS or quantile regressions present significant results, we can confirm that swap derivatives are positively associated with firm value. At the same time, forwards and options do not show any significant relationship. Additionally, we find that the relationship between currency derivative instrument usage and firm value varies across quantiles. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not always statistically significant.

Table 5.7: Baseline and Quantile Regressions: Currency Derivative Instruments

This table shows the impact of Currency Derivative Instruments Usage on firm value for the sample with sales and operations bearing voalitile foreign exchange rate. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Currency Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 181 unique firms, listed in Oslo Stock Exchange, and comprises 1,767 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Forward	0.0111	0.0029	0.0042	0.0068	0.0107	0.0152	0.0187	0.0207
	(0.17)	(0.04)	(0.07)	(0.11)	(0.16)	(0.18)	(0.19)	(0.19)
Option	-0.0936	-0.1582	-0.1474	-0.1274	-0.0963	-0.0610	-0.0337	-0.0174
	(-1.23)	(-1.44)	(-1.43)	(-1.37)	(-1.19)	(-0.81)	(-0.43)	(-0.21)
Swap	**0.1283***	**0.1268***	**0.1270***	**0.1275***	**0.1282***	0.1291	0.1297	0.1301
	(1.76)	(1.71)	(1.75)	(1.77)	(1.72)	(1.57)	(1.43)	(1.34)
Liq	**0.0120*****	0.0156	0.0150	0.0139	**0.0122***	**0.0102***	0.0086	0.0077
	(2.92)	(1.30)	(1.37)	(1.49)	(1.71)	(1.87)	(1.60)	(1.29)
Curr	**-0.0134*****	**-0.0170****	**-0.0164****	**-0.0153****	**-0.0136*****	**-0.0116*****	**-0.0101****	**-0.0092***
	(-3.05)	(-1.98)	(-2.09)	(-2.29)	(-2.64)	(-2.78)	(-2.31)	(-1.88)
Lev	0.1279	0.1294	0.1291	0.1287	0.1280	0.1272	0.1266	0.1262
	(1.13)	(0.84)	(0.87)	(0.90)	(0.89)	(0.81)	(0.71)	(0.66)
ROA	**-0.0407*****	-0.0488	-0.0475	-0.0450	-0.0411	-0.0367	-0.0332	-0.0312
	(-6.10)	(-0.58)	(-0.61)	(-0.64)	(-0.65)	(-0.57)	(-0.47)	(-0.40)
Size	**-0.1497*****	**-0.0881****	**-0.0984*****	**-0.1174*****	**-0.1470*****	**-0.1807*****	**-0.2067*****	**-0.2223*****
	(-4.25)	(-2.31)	(-2.69)	(-3.31)	(-4.09)	(-4.61)	(-4.78)	(-4.74)
Tangibility	-0.1046	-0.1656	-0.1554	-0.1365	-0.1072	-0.0739	-0.0481	-0.0327
	(-0.62)	(-1.06)	(-0.99)	(-0.83)	(-0.57)	(-0.32)	(-0.18)	(-0.11)
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,767	1,767	1,767	1,767	1,767	1,767	1,767	1,767
R^2	0.24							

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.4 Commodity Derivative Instruments

In Table 5.8, we present the fixed effect OLS and quantile regression estimates by analyzing the use of commodity derivative instruments for the firms with commodity price exposure. In other words, for the selected firms exposed to floating commodity price risks. All the quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the OLS results, our findings indicate positive relationships between all instruments and firm value. However, these relationships are not statistically significant. Notably, the relationship between options and firm value is significantly positive below the 10th quantile.

The quantile results differ from those obtained using the fixed effect OLS regression. Additionally, certain control variables demonstrate the significance and exhibit the expected signs. Based on the effects of covariates, we find that firm size (log of total assets) has a negative and significant association at the 10 percent level with firm value. In contrast, the ROA exhibits a negative relationship at the average level, contrary to the expectation that more profitable firms would have a higher value. Notably, this association is primarily observed in the OLS estimation, with no significant relationships detected across quantiles. On the other hand, the leverage ratio demonstrates strong positive relationships at the mean and the quantiles below the median.

Although not all OLS or quantile regressions present significant results, we can confirm that option derivatives are positively associated with firm value. At the same time, forwards and swaps do not show any significant relationship. Additionally, we find that the relationship between commodity derivative instrument usage and firm value varies across quantiles. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not always statistically significant.

Table 5.8: Baseline and Quantile Regressions: Commodity Derivative Instruments

This table shows the impact of Commodity Derivative Instruments Usage on firm value for the sample with sales bearing floating commodity price. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Commodity Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 111 unique firms, listed in Oslo Stock Exchange, and comprises 1,148 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Forward	0.0442	0.0726	0.0671	0.0588	0.0463	0.0303	0.0193	0.0114
	(0.69)	(1.06)	(1.06)	(1.00)	(0.74)	(0.38)	(0.20)	(0.10)
Option	0.1762	**0.2506***	**0.2362***	0.2144	0.1817	0.1396	0.1108	0.0902
	(0.90)	(1.77)	(1.66)	(1.42)	(1.01)	(0.60)	(0.40)	(0.29)
Swap	0.1009	0.0819	0.0856	0.0912	0.0995	0.1103	0.1176	0.1229
	(1.26)	(0.82)	(0.94)	(1.11)	(1.22)	(1.09)	(0.95)	(0.85)
Liq	0.0023	0.0130	0.0109	0.0078	0.0031	-0.0029	-0.0071	-0.0100
	(0.29)	(0.53)	(0.49)	(0.40)	(0.20)	(-0.23)	(-0.52)	(-0.66)
Curr	-0.0036	-0.0144	-0.0123	-0.0091	-0.0044	0.0017	0.0058	0.0088
	(-0.44)	(-0.91)	(-0.84)	(-0.71)	(-0.40)	(0.16)	(0.51)	(0.70)
Lev	**0.3046***	**0.5505*****	**0.5029*****	**0.4309*****	**0.3228****	0.1837	0.0885	0.0203
	(1.90)	(2.99)	(2.86)	(2.59)	(1.99)	(1.07)	(0.46)	(0.10)
ROA	**-0.0449*****	-0.0538	-0.0521	-0.0495	-0.0456	-0.0406	-0.0371	-0.0347
	(-6.68)	(-0.47)	(-0.46)	(-0.44)	(-0.40)	(-0.33)	(-0.28)	(-0.25)
Size	**-0.0821***	-0.0377	-0.0463	-0.0593	**-0.0788***	**-0.1040****	**-0.1212****	**-0.1335****
	(-1.94)	(-0.85)	(-1.08)	(-1.42)	(-1.84)	(-2.17)	(-2.24)	(-2.23)
Tangibility	-0.2342	-0.2735	-0.2659	-0.2543	-0.2371	-0.2149	-0.1997	-0.1888
	(-1.35)	(-1.47)	(-1.50)	(-1.48)	(-1.34)	(-1.07)	(-0.87)	(-0.74)
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,148	1,148	1,148	1,148	1,148	1,148	1,148	1,148
R^2	0.19							

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Time Heterogeneity Test

5.3.1 Derivative Usage

In Table 5.9, we present the fixed effect OLS and quantile regression estimates by analyzing the use of any derivative in different time intervals for the firms with floating interest rate, foreign exchange, and commodity price exposure. In other words, for the selected firms that face any risk exposure. All the quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the OLS results, we find positive relationships between derivatives and firm value during the periods 2007-2009, 2013-2015, and 2016-2018, as well as across all quantile estimates. However, it is important to note that these relationships do not reach statistical significance. On the contrary, from 2019 to 2021, we observe negative and statistically insignificant relationships between derivatives and firm value. Notably, in 2010-2012, we found negative and statistically significant relationships between derivatives and firm value, as evidenced by both the OLS and the quantile estimates at the 25th, 50th, 75th, and 90th levels.

The interesting finding is the observed significant negative relationship between derivative usage and firm value during 2010-2012, compared to the insignificant positive relationship during 2007-2009. The aftermath of the global financial crisis, characterized by economic uncertainty and tighter credit conditions, likely influenced firms' cautious approach towards derivative usage, potentially resulting in less effective risk management practices and negative impacts on firm value. Meanwhile, the volatile and uncertain market conditions prevalent in 2019-2021, including trade disputes, geopolitical tensions, and the COVID-19 pandemic, likely impacted the effectiveness of derivative strategies and their influence on firm value. Conversely, the relative stability in market conditions during the earlier periods, 2013-2015 and 2016-2018 may have allowed firms to leverage derivatives more effectively. Additionally, we find that the relationship between derivative usage and firm value varies across quantiles for different time intervals. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not statistically significant.

Table 5.9: Baseline and Quantile Regressions: Derivatives Usage

This table shows the impact of General Derivative Usage on firm value in different time intervals for the sample with bearing floating interest rate exposure, currency exposure and commodity price exposure. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 183 unique firms, listed in Oslo Stock Exchange, and comprises 1,819 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
2007-2009								
Dev	0.1583	0.1923	0.1885	0.1804	0.1593	0.1353	0.1265	0.1239
	(0.94)	(1.08)	(1.07)	(1.01)	(0.80)	(0.55)	(0.48)	(0.45)
Fit statistics								
Observations	261	261	261	261	261	261	261	261
R^2	0.49							
2010-2012								
Dev	**-0.1479*****	-0.1113	-0.1137	**-0.1253***	**-0.1481****	**-0.1711***	**-0.1852***	-0.1902
	(-2.85)	(-1.21)	(-1.40)	(-1.79)	(-2.13)	(-1.81)	(-1.66)	(-1.48)
Fit statistics								
Observations	297	297	297	297	297	297	297	297
R^2	0.71							
2013-2015								
Dev	0.0313	0.0760	0.0578	0.0517	0.0324	0.0126	0.0050	-0.0023
	(0.22)	(0.44)	(0.35)	(0.32)	(0.19)	(0.07)	(0.02)	(-0.01)
Fit statistics								
Observations	347	347	347	347	347	347	347	347
R^2	0.14							
2016-2018								
Dev	0.0692	0.0595	0.0607	0.0637	0.0680	0.0748	0.0775	0.0791
	(0.60)	(0.29)	(0.32)	(0.37)	(0.48)	(0.66)	(0.72)	(0.74)
Fit statistics								
Observations	404	404	404	404	404	404	404	404
R^2	0.62							
2019-2021								
Dev	-0.0510	-0.0907	-0.0775	-0.0681	-0.0518	-0.0342	-0.0278	-0.0252
	(-0.67)	(-0.71)	(-0.69)	(-0.68)	(-0.64)	(-0.53)	(-0.45)	(-0.41)
Fit statistics								
Observations	510	510	510	510	510	510	510	510
R^2	0.13							
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3.2 Interest Rate Derivatives

In Table 5.10, we present the fixed effect OLS and quantile regression estimates by analyzing the use of interest rate derivatives in different time intervals for the firms with interest rate exposure only. In other words, for the selected firms with exposure to floating interest rates. All the quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the results, our findings reveal positive relationships between interest rate derivatives and firm value during 2007-2009 and 2013-2015 for OLS estimates and all quantiles. However, it is worth noting that the relationships are statistically significant for the OLS and 75th and 90th quantiles in 2007-2009 only, while they did not reach statistical significance in 2013-2015. Conversely, our analysis demonstrates negative and insignificant relationships between interest rate derivatives and firm value during 2010-2012, 2016-2018, and 2019-2021.

The interesting finding is the observed significant positive relationship between interest rate derivative usage and firm value during 2007-2009, compared to the insignificant relationships during other periods. This period was marked by the global financial crisis, which profoundly affected the economy and financial markets. The unique market conditions during this period, characterized by economic turmoil and regulatory responses, may have influenced the effectiveness of interest rate derivatives as risk management tools and their impact on firm value. Notably, firms positioned at the higher end of the firm value distribution had significant positive relationships between interest rate derivative usage and firm value, potentially reflecting their effective risk management in mitigating floating interest rate exposure. Additionally, we find that the relationship between interest rate derivative usage and firm value varies across quantiles for different time intervals. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not always statistically significant.

Table 5.10: Baseline and Quantile Regressions: Interest Rate Derivative

This table shows the impact of Interest Rate Derivative Usage on firm value in different time intervals for the sample with liabilities bearing floating interest rate. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Interest Rate Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 164 unique firms, listed in Oslo Stock Exchange, and comprises 1,446 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
2007-2009								
Interest_Dev	**0.1085****	0.0558	0.0609	0.0751	0.1074	**0.1453***	**0.1578***	0.1642
	(2.11)	(0.33)	(0.41)	(0.61)	(1.32)	(1.90)	(1.67)	(1.50)
Fit statistics								
Observations	213	213	213	213	213	213	213	213
R^2	0.60							
2010-2012								
Interest_Dev	-0.0293	-0.0315	-0.0314	-0.0307	-0.0294	-0.0277	-0.0272	-0.0269
	(-0.56)	(-0.42)	(-0.43)	(-0.45)	(-0.46)	(-0.45)	(-0.44)	(-0.42)
Fit statistics								
Observations	234	234	234	234	234	234	234	234
R^2	0.46							
2013-2015								
Interest_Dev	0.1924	0.1398	0.1642	0.1715	0.1895	0.2128	0.2201	0.2272
	(1.10)	(0.79)	(0.99)	(1.06)	(1.17)	(1.20)	(1.16)	(1.03)
Fit statistics								
Observations	271	271	271	271	271	271	271	271
R^2	0.16							
2016-2018								
Interest_Dev	-0.0852	-0.0788	-0.0796	-0.0813	-0.0842	-0.0894	-0.0912	-0.0917
	(-1.48)	(-1.07)	(-1.15)	(-1.27)	(-1.41)	(-1.36)	(-1.28)	(-1.21)
Fit statistics								
Observations	308	308	308	308	308	308	308	308
R^2	0.49							
2019-2021								
Interest_Dev	-0.0602	-0.0413	-0.0469	-0.0513	-0.0608	-0.0695	-0.0728	-0.0735
	(-1.15)	(-0.44)	(-0.58)	(-0.71)	(-1.03)	(-1.31)	(-1.34)	(-1.34)
Fit statistics								
Observations	420	420	420	420	420	420	420	420
R^2	0.17							
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3.3 Currency Derivatives

In Table 5.11, we present the fixed effect OLS and quantile regression estimates by analyzing the use of currency derivatives in different time intervals for the firms with currency exposure. In other words, for the selected firms exposed to floating foreign exchange risks. All the quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the OLS results, our findings suggest positive relationships between currency derivatives and firm value during 2007-2009, 2013-2015, and 2019-2021. However, it is important to note that these relationships do not reach statistical significance for the OLS estimates or the quantile regressions across any quantiles. In contrast, our results indicate negative relationships between currency derivatives and firm value during 2010-2012 and 2016-2018. Among these periods, only the relationship in 2010-2012 achieved statistical significance for the 10th and 25th quantile regressions.

Specifically, we observe a statistically significant positive relationship in the 10th and 25th quantile regressions during 2010-2012. This indicates that firms positioned at the lower end of the firm value distribution have significant negative relationships between currency derivative usage and firm value, potentially reflecting their ineffective risk management in mitigating floating exchange rate exposure. Meanwhile, our analysis reveals a dynamic shift in the direction of these relationships, transitioning from positive to negative, negative to positive, positive to negative, and negative to positive across the five periods. This suggests that the potential impact of currency derivatives on firm value is inconsistent over time. Additionally, we find that the relationship between currency derivative usage and firm value varies across quantiles for different time intervals. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not always statistically significant.

Table 5.11: Baseline and Quantile Regressions: Currency Derivative

This table shows the impact of Currency Derivative Usage on firm value in different time intervals for the sample with sales and operations bearing voalitile foreign exchange rate. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Currency Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 181 unique firms, listed in Oslo Stock Exchange, and comprises 1,767 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
2007-2009								
Currency_Dev	0.1443	0.0479	0.0631	0.0844	0.1443	0.2068	0.2347	0.2425
	(1.11)	(0.38)	(0.51)	(0.68)	(1.04)	(1.17)	(1.20)	(1.19)
Fit statistics								
Observations	252	252	252	252	252	252	252	252
R^2	0.50							
2010-2012								
Currency_Dev	-0.1003	-0.1349	**-0.1324***	**-0.1211***	-0.0970	-0.0779	-0.0675	-0.0633
	(-1.44)	(-1.63)	(-1.70)	(-1.71)	(-1.47)	(-1.02)	(-0.79)	(-0.68)
Fit statistics								
Observations	283	283	283	283	283	283	283	283
R^2	0.71							
2013-2015								
Currency_Dev	0.0052	0.0532	0.0411	0.0327	0.0071	-0.0202	-0.0320	-0.0507
	(0.05)	(0.39)	(0.34)	(0.29)	(0.06)	(-0.14)	(-0.19)	(-0.26)
Fit statistics								
Observations	333	333	333	333	333	333	333	333
R^2	0.14							
2016-2018								
Currency_Dev	-0.0110	-0.0758	-0.0634	-0.0458	-0.0190	0.0218	0.0389	0.0454
	(-0.15)	(-0.85)	(-0.73)	(-0.55)	(-0.24)	(0.27)	(0.47)	(0.52)
Fit statistics								
Observations	396	396	396	396	396	396	396	396
R^2	0.62							
2019-2021								
Currency_Dev	0.0668	0.0795	0.0758	0.0728	0.0670	0.0608	0.0585	0.0582
	(1.00)	(0.61)	(0.67)	(0.73)	(0.88)	(1.07)	(1.10)	(1.11)
Fit statistics								
Observations	503	503	503	503	503	503	503	503
R^2	0.14							
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3.4 Commodity Derivatives

In Table 5.12, we present the fixed effect OLS and quantile regression estimates by analyzing the use of commodity derivatives in different time intervals for the firms with commodity price exposure. In other words, for the selected firms exposed to floating commodity price risks. All the quantile regression results are presented at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles. Based on the OLS results, our findings indicate positive relationships between commodity derivatives and firm value during 2007-2009, 2013-2015, and 2016-2018. These relationships are consistent across all OLS estimates and quantiles, with statistically significant coefficients observed for the 2016-2018 period in the OLS and quantile estimates up to the 50th percentile. However, contrasting patterns emerged between 2010-2012 and 2019-2021, where negative relationships between commodity derivatives and firm values are observed. Notably, the negative relationship in 2019-2021 achieves statistical significance for the OLS and quantile estimates at the 75th and 90th percentiles.

The findings reveal a significant positive relationship between commodity derivative usage and firm value during 2016-2018 for firms up to the 50th percentile of the firm value distribution. This suggests that these firms effectively managed their floating exchange rate exposure through commodity derivative usage, potentially enhancing firm value. However, from 2019 to 2021, a significant negative relationship is observed for firms at the 75th and 90th percentiles of the firm value distribution. This indicates that firms in higher quantiles possibly experience a negative impact on firm value when utilizing commodity derivatives. Additionally, the relationship between commodity derivative usage and firm value varies across quantiles for different time intervals. This finding aligns with our expectation to conduct quantile analysis, even though the relationships are not always statistically significant.

Table 5.12: Baseline and Quantile Regressions: Commodity Derivative

This table shows the impact of Commodity Derivative Usage on firm value in different time intervals for the sample with sales bearing floating commodity price. Pooled simultaneous quantile regression of Ln(Tobin's Q) on firm-specific factors and time-dummies. Explanatory variables include Commodity Derivative Usage dummies, Liquidity ratio, Current ratio, Leverage, Return on Assets, lSize, Tangibility and time-dummies. The sample includes 111 unique firms, listed in Oslo Stock Exchange, and comprises 1,148 yearly observations, from year 2007 to 2021. Coefficients and robust t-statistics are reported from Fixed-effects OLS regression and for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The t-statistics for quantile regression are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications.

	FE	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
2007-2009								
Commodity_Dev	0.0197	0.1152	0.0929	0.0717	0.0238	-0.0396	-0.0616	-0.0688
	(0.14)	(0.75)	(0.62)	(0.49)	(0.15)	(-0.22)	(-0.31)	(-0.32)
Fit statistics								
Observations	177	177	177	177	177	177	177	177
R^2	0.51							
2010-2012								
Commodity_Dev	-0.0151	-0.0551	-0.0510	-0.0396	-0.0140	0.0121	0.0277	0.0354
	(-0.29)	(-0.46)	(-0.47)	(-0.42)	(-0.20)	(0.18)	(0.36)	(0.36)
Fit statistics								
Observations	198	198	198	198	198	198	198	198
R^2	0.81							
2013-2015								
Commodity_Dev	0.0685	-0.0218	-0.0117	0.0138	0.0616	0.1294	0.1577	0.1770
	(0.34)	(-0.08)	(-0.05)	(0.06)	(0.29)	(0.61)	(0.72)	(0.74)
Fit statistics								
Observations	221	221	221	221	221	221	221	221
R^2	0.15							
2016-2018								
Commodity_Dev	**0.2739****	**0.4259***	**0.4085***	**0.3659***	**0.2816****	0.1695	0.1299	0.1100
	(2.43)	(1.79)	(1.89)	(1.94)	(1.97)	(1.57)	(1.21)	(0.98)
Fit statistics								
Observations	245	245	245	245	245	245	245	245
R^2	0.74							
2019-2021								
Commodity_Dev	**-0.1635***	-0.1210	-0.1299	-0.1403	-0.1617	**-0.1868***	**-0.1963***	-0.1989
	(-1.90)	(-0.96)	(-1.14)	(-1.29)	(-1.52)	(-1.67)	(-1.68)	(-1.61)
Fit statistics								
Observations	307	307	307	307	307	307	307	307
R^2	0.13							
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.4 Difference-in-Difference: Event Study

5.4.1 Derivative Usage

In this study, we seek to understand the impact of derivative usage on firm value with various exposures. To estimate the causal effect, we compare periods when firms utilize derivatives to periods they do not. Specifically, we designate the first year of derivative implementation as Year 0, with the preceding year as Year -1 for reference. Our sample consists of 822 observations, encompassing 89 unique firms, each containing at least one non-treatment period.

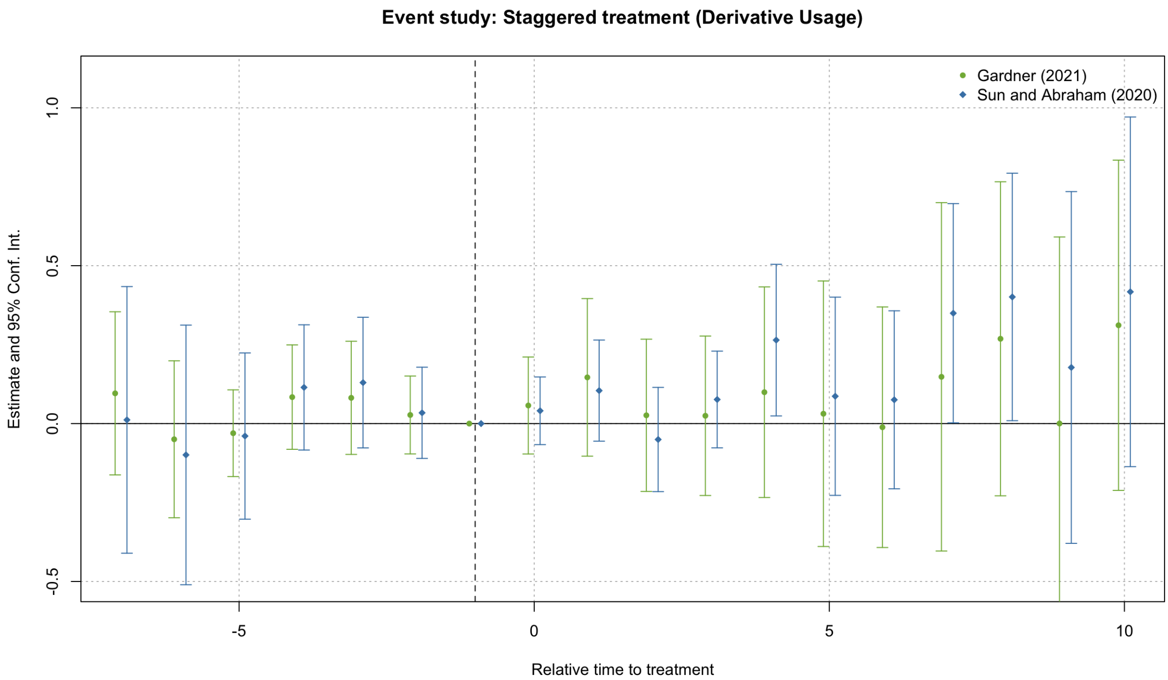

Figure 5.1: Difference-in-Difference event study on Derivative Usage

The dynamic difference-in-difference model shows no significant differences between the treatment and control groups six years before treatment. However, there are statistically significant positive coefficients at the 95% confidence level in Year 4, Year 7, and Year 8 according to the Sun & Abraham (2020) estimator, indicating a positive impact of the treatment on firm value.

Figure 5.1 provides insights into the parallel trend analysis. According to the Sun & Abraham (2020) estimator, there are no substantial differences between the treatment and control firms for the six or seven years before the treatment. However, after the treatment, there is an observable increase in changes. Meanwhile, several years show significant positive effects. This suggests that general derivative usage does not immediately impact changes in firm value, Ln(Tobin's Q), but rather a delayed effect. Although the Gardner (2021) estimate does not exhibit statistical significance, the positive coefficients also indicate a potential positive impact of derivative usage on firm value.

Referring to Table 5.13, which only reveals the several years surrounding Year -1 due to space limitations, we observe that the treatment and control groups exhibit insignificant positive coefficients in all three models. However, in Model (2), the coefficient of Year 4 becomes significantly positive, indicating a notable difference between the control and treatment groups. Also, the coefficient of the average treatment effect for the treated (ATT) is significantly positive, which means that the observed effect is unlikely to have occurred by chance. Regarding the control variables, lSize (firm size) and ROA are significantly negative in Model (2) and Model (3), which both include time and firm fixed effects. In contrast, Model (1) only estimates treatment effects using a different algorithm. From the interpretation of Model (2) results, we conclude that changes in Ln(Tobin's Q) are highly negatively associated with firm size and ROA. This suggests that larger firms may face higher capital costs and potentially exhibit lower efficiency in deploying assets and investing in growth opportunities.

The insights from the analysis indicate that utilizing derivative tools in alignment with their respective exposures can enhance firms' operational efficiency, not by chance, but with lagged effects. However, it should be noted that not all derivatives contribute equally to a firm's value creation. In the next analysis, we aim to explore the impact of interest rates, currency, and commodity derivatives, thereby expanding our understanding of their potential effects.

Table 5.13: DiD Event study: Staggered treatment (Derivative Usage)

This table shows the impact of General Derivative Usage on firm value for the sample with exposure to floating interest rate exposure, currency exposure and commodity price exposure. Difference-in-Difference event study is applied to this sample using Ln(Tobin's Q) as dependent variable with firm-specific factors as covariates combining with company and time fixed effects. Covariates include Leverage Ratio, Firm Size, Return on Assets, Liquidity Ratio, Current Ratio and Tangibility. The sample includes 89 unique firms, listed in Oslo Stock Exchange, and comprises 822 yearly observations, from year 2007 to 2021. Coefficients and robust standard errors are reported using different estimators. Model (1) is estimated by Gardner (2021), Model (2) is estimated by Sun and Abraham (2020) and Model (3) is estimated by Two-way fixed effects.

Dependent Variable		Ln(Tobin's Q)	
Model	(1)	(2)	(3)
Lev	0.0069	0.0744	0.1167
	(0.0202)	(0.1261)	(0.1349)
lSize	0.0063	**-0.1977*****	**-0.1775*****
	(0.0039)	(0.0586)	(0.0517)
ROA	0.0047	**-0.0496*****	**-0.0391*****
	(0.0038)	(0.0114)	(0.0077)
Liq	0.00001	0.0038	0.0031
	(0.0005)	(0.0080)	(0.0068)
Curr	-0.0001	-0.0049	-0.0044
	(0.0005)	(0.0083)	(0.0071)
Tangibility	**-0.1615***	0.1020	0.0010
	(0.0824)	(0.2650)	(0.2240)
Year = -3	0.0815	0.1298	0.1230
	(0.0914)	(0.1056)	(0.1518)
Year = -2	0.0273	0.0341	0.0717
	(0.0629)	(0.0737)	(0.1032)
Year = 0	0.0573	0.0405	0.0501
	(0.0783)	(0.0547)	(0.0822)
Year = 1	0.1463	0.1044	0.1389
	(0.1273)	(0.0817)	(0.1230)
Year = 2	0.0262	-0.0504	0.0013
	(0.1230)	(0.0842)	(0.1010)
Year = 3	0.0248	0.0763	0.0109
	(0.1288)	(0.0781)	(0.0980)
Year = 4	0.0994	**0.2644****	0.1661
	(0.1702)	(0.1225)	(0.1497)
ATT		**0.1140***	
		(0.0662)	
Fixed-effects			
Company	No	Yes	Yes
Year	No	Yes	Yes
Fit statistics			
Observations	822	822	822
R^2	0.03	0.83	0.78
Within R^2		0.36	0.17

standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.4.2 Interest Rate Derivatives

In this study, we examine the impact of interest rate derivatives on firm value when firms are exposed to floating interest rate risk. We estimate the causal effect by comparing periods when firms utilize interest rate derivatives to periods they do not. As previously defined, Year 0 represents the first year of interest rate derivative implementation, while Year -1 serves as the reference year. Our sample comprises 754 observations, encompassing 98 unique firms, each containing at least one non-treatment period. This analysis allows us to gain insights into the effects of interest rate derivatives on firm value in the context of floating interest rate exposure.

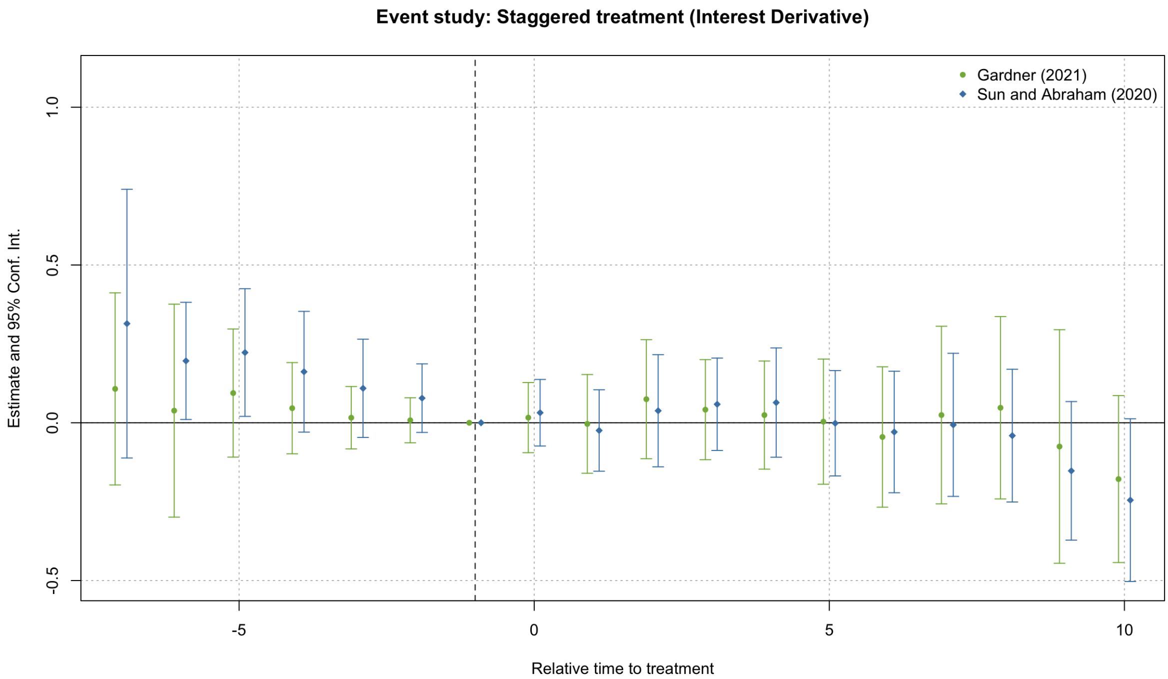

Figure 5.2: Difference-in-Difference event study on Interest rate Derivatives

The dynamic difference-in-difference model shows potentially significant differences between the treatment and control groups six years before treatment. However, there are no statistically significant coefficients at the 95% confidence level in years after the treatment according to the Sun & Abraham (2020) estimator, indicating no impact of the treatment on firm value.

Figure 5.2 presents the findings from the parallel trend analysis. Before treatment, as estimated by Gardner (2021), there are no significant differences between the treatment and control firms for six or seven years. However, under the Sun & Abraham (2020) estimator, several years show significant positive effects before treatment. Following the treatment year, both estimators indicate a change decrease, with consistently negative coefficients after five years. In the post-treatment period, the fluctuation in changes is smaller, with most years showing values around zero but lacking significant effects. This suggests that the usage of interest rate derivatives does not have a noticeable impact on Ln(Tobin's Q) at a 95% confidence interval, but it potentially reduces fluctuations. Gardner's (2021) and Sun & Abraham's (2020) estimates indicate that using interest rate derivatives for an extended period could have negative effects after ten years at the 90 percent confidence level. One possible explanation is that some firms in Norway implemented derivatives much earlier than the continuously decreasing interest rates in the Norwegian capital market during the sample period, leading to potential inefficiencies in their floating interest rate hedging strategies.

Let us look at Table 5.14, where we only keep the years around Year -1 due to space limitation. We can learn that both years around Year -1 have insignificant coefficients around zero in all three models. Also, it reveals that, in general, interest rate derivatives would have an insignificant zero effect on Ln(Tobin's Q). The coefficient of the average treatment effect for the treated (ATT) is insignificantly negative, which means that the treatment effect is not obvious but potentially negative. Regarding control variables, we find that leverage (Lev) and the current ratio (Curr) appear significant in Model (2). In terms of interpretation, we observe that when firms face floating interest rate exposure, a firm's leverage ratio and current ratio play a significant role in firm value. Specifically, a higher proportion of liabilities and a lower proportion of cash and cash equivalent holdings are associated with potential value creation. This finding challenges the predictions of the pecking order theory, which suggests a negative relationship between leverage and firm performance due to agency costs between owners and lenders. However, in Norway, managers may prioritize the productivity of capital obtained through debt financing when confronted with floating interest rate exposure.

Table 5.14: DiD Event study: Staggered treatment (Interest Rate Derivative)

This table shows the impact of Interest Derivative on firm value for the sample with exposure to floating interest rate exposure only. Difference-in-Difference event study is applied to this sample using Ln(Tobin's Q) as dependent variable with firm-specific factors as covariates combining with company and time fixed effects. Covariates include Leverage Ratio, Firm Size, Return on Assets, Liquidity Ratio, Current Ratio and Tangibility. The sample includes 98 unique firms, listed in Oslo Stock Exchange, and comprises 754 yearly observations, from year 2007 to 2021. Coefficients and robust standard errors are reported using different estimators. Model (1) is estimated by Gardner (2021), Model (2) is estimated by Sun and Abraham (2020) and Model (3) is estimated by Two-way fixed effects.

Dependent Variable		Ln(Tobin's Q)	
Model	(1)	(2)	(3)
Lev	-0.0405	**0.4086****	**0.3443****
	(0.0440)	(0.1722)	(0.1692)
lSize	**0.0081***	-0.0376	-0.0464
	(0.0048)	(0.0475)	(0.0428)
ROA	0.0185	0.0053	-0.0004
	(0.0278)	(0.0894)	(0.0802)
Liq	-0.0029	0.0074	0.0076
	(0.0027)	(0.0100)	(0.0094)
Curr	0.0004	**-0.0062***	-0.0059
	(0.0012)	(0.0037)	(0.0037)
Tangibility	**-0.1349***	-0.0745	-0.0424
	(0.0751)	(0.2009)	(0.1842)
Year = -3	0.0161	0.1092	0.0902
	(0.0504)	(0.0794)	(0.1159)
Year = -2	0.0079	0.0780	0.0615
	(0.0364)	(0.0554)	(0.0875)
Year = 0	0.0164	0.0318	0.0724
	(0.0567)	(0.0538)	(0.0565)
Year = 1	-0.0036	-0.0244	0.0353
	(0.0799)	(0.0659)	(0.0669)
Year = 2	0.0747	0.0381	0.0796
	(0.0962)	(0.0906)	(0.0833)
Year = 3	0.0415	0.0586	0.0884
	(0.0809)	(0.0747)	(0.0681)
Year = 4	0.0244	0.0640	0.0948
	(0.0874)	(0.0884)	(0.0659)
ATT		-0.0040	
		(-0.0634)	
Fixed-effects			
Company	No	Yes	Yes
Year	No	Yes	Yes
Fit statistics			
Observations	744	753	754
R^2	0.03	0.85	0.81
Within R^2		0.27	0.06

standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.4.3 Currency Derivatives

This study examines the impact of currency derivatives on firm value when firms are exposed to foreign exchange rate risks. We estimate the causal effect by comparing periods when firms utilize currency derivatives to periods they do not. As previously defined, Year 0 represents the first year of currency derivative implementation, while Year -1 is the reference year. Our sample consists of 981 observations, encompassing 110 unique firms, each containing at least one non-treatment period. This analysis allows us to investigate the effects of currency derivatives on firm value in the context of floating foreign exchange exposure.

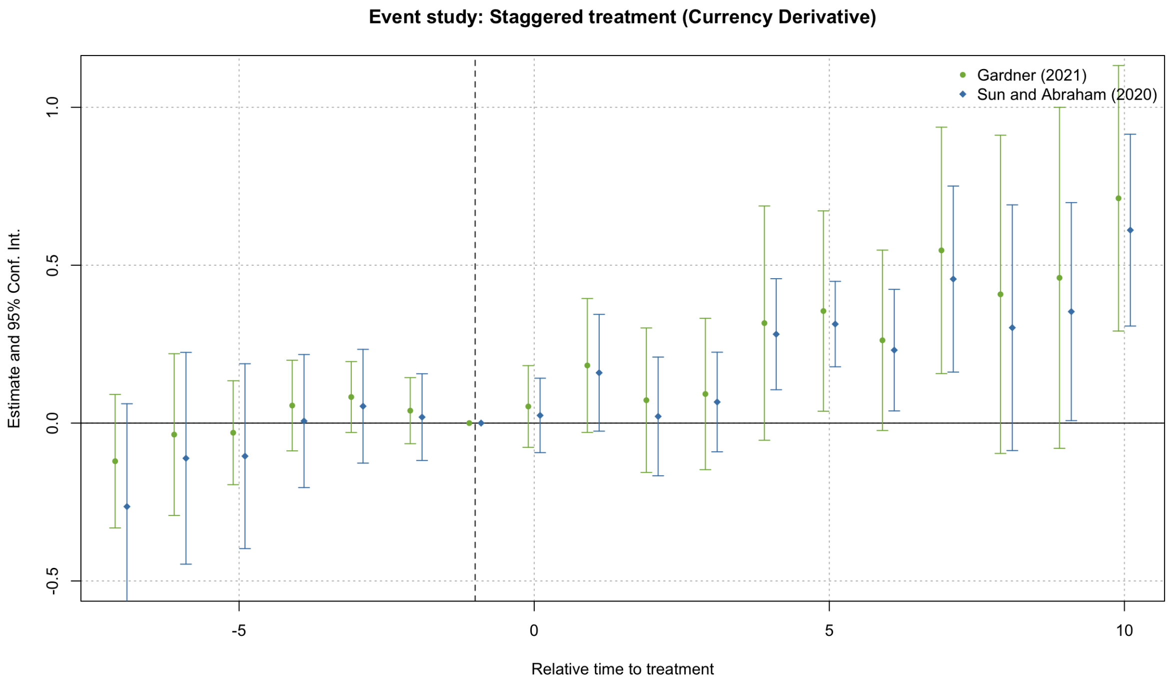

Figure 5.3: Difference-in-Difference event study on Currency Derivatives

The dynamic difference-in-difference model shows no significant differences between the treatment and control groups six years before treatment. However, there are statistically significant positive coefficients at the 95% confidence level in Year 4, Year 5, Year 6, Year 7, and Year 10 according to the Sun & Abraham (2020) estimator, indicating a positive impact of the treatment on firm value.

Figure 5.3 presents the findings from the parallel trend analysis. As indicated by both estimators, there is virtually no difference between the treatment and control firms during the six or seven years prior to treatment. However, changes start to increase after the treatment for both groups, with significant positive coefficients emerging after four years. In the post-treatment period, changes consistently show positive fluctuations. In contrast, the pre-treatment group exhibits negative coefficients, indicating a noticeable positive effect of currency derivatives on changes in Ln(Tobin's Q). The Gardner (2021) and Sun & Abraham (2020) estimators support this finding, suggesting that extended usage of currency derivatives leads to positive effects. This can be attributed to the high exposure of Norwegian firms to foreign currency, given the reliance on exports and the fact that the NOK is not the primary currency.

Table 5.15, focusing on the years around Year -1 due to space limitations, reveals that both years around Year -1 exhibit insignificant coefficients near zero across all three models. However, the overall analysis suggests that currency derivatives significantly affect Ln(Tobin's Q). Additionally, the coefficient of the average treatment effect for the treated (ATT) is significantly positive, indicating that the observed effect is unlikely to be by chance. Examining the control variables in Model (2), we find that firm size (lSize), ROA, the liquidity ratio (Liq), and the current ratio (Curr) are significant. In terms of interpretation, when firms employ currency derivatives to hedge foreign exposure, firm size, ROA, the liquidity ratio, and the current ratio have strong positive relationships with firm value. Smaller firm sizes, a lower proportion of sales, a higher proportion of current assets, and a lower proportion of cash and cash equivalent holdings are associated with higher firm value. This may be attributed to larger firms' sales and currency values being highly influenced by floating foreign exchange rates.

Therefore, the insights we observe are that investments in currency derivatives could help firms perform more efficiently, and the effects of foreign currency derivatives are significant after several years. The impact of exchange rate fluctuations on a firm's financial performance may not be immediate, and it may take some time for the effects of currency derivatives to reflect in the firm's financial results.

Table 5.15: DiD Event study: Staggered treatment (Currency Derivative)

This table shows the impact of Currency Derivative on firm value for the sample with exposure to currency exchange exposure only. Difference-in-Difference event study is applied to this sample using Ln(Tobin's Q) as dependent variable with firm-specific factors as covariates combining with company and time fixed effects. Covariates include Leverage Ratio, Firm Size, Return on Assets, Liquidity Ratio, Current Ratio and Tangibility. The sample includes 110 unique firms, listed in Oslo Stock Exchange, and comprises 981 yearly observations, from year 2007 to 2021. Coefficients and robust standard errors are reported using different estimators. Model (1) is estimated by Gardner (2021), Model (2) is estimated by Sun and Abraham (2020) and Model (3) is estimated by Two-way fixed effects.

Dependent Variable:		Ln(Tobin's Q)	
Model:	(1)	(2)	(3)
Lev	0.0150	0.0998	0.0905
	(0.0175)	(0.1281)	(0.1184)
lSize	0.0022	**-0.2079*****	**-0.1879*****
	(0.0021)	(0.0408)	(0.0421)
ROA	0.0018	**-0.0328*****	**-0.0372*****
	(0.0019)	(0.0083)	(0.0077)
Liq	-0.0009	**0.0125****	**0.0120*****
	(0.0009)	(0.0055)	(0.0041)
Curr	0.0009	**-0.0138****	**-0.0134*****
	(0.0009)	(0.0058)	(0.0043)
Tangibility	**-0.0695***	-0.1641	-0.0945
	(0.0387)	(0.2679)	(0.2296)
Year = -3	0.0826	0.0534	0.0478
	(0.0573)	(0.0919)	(0.1082)
Year = -2	0.0394	0.0189	0.0111
	(0.0534)	(0.0701)	(0.0863)
Year = 0	0.0526	0.0243	0.0024
	(0.0660)	(0.0601)	(0.0722)
Year = 1	**0.1825***	**0.1594***	0.1338
	(0.1082)	(0.0944)	(0.1086)
Year = 2	0.0724	0.0211	0.0327
	(0.1167)	(0.0959)	(0.1095)
Year = 3	0.0922	0.0668	0.0543
	(0.1223)	(0.0804)	(0.1069)
Year = 4	**0.3166***	**0.2815*****	0.2605
	(0.1893)	(0.0897)	(0.1694)
ATT		**0.1381****	
		(0.0629)	
Fixed-effects			
Company	No	Yes	Yes
Year	No	Yes	Yes
Fit statistics			
Observations	980	981	981
R^2	0.06	0.83	0.80
Within R^2		0.36	0.22

standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.4.4 Commodity Derivatives

In this analysis, we investigate the impact of commodity derivatives on firm value when firms are exposed to commodity price risks. We estimate the causal effect by comparing periods when firms utilize commodity derivatives to periods they do not. As previously defined, Year 0 represents the first year of commodity derivative implementation, while Year -1 is the reference year. Our sample consists of 949 observations, encompassing 90 unique firms, each containing at least one non-treatment period. This analysis allows us to examine the effects of commodity derivatives on firm value in the context of commodity price exposure.

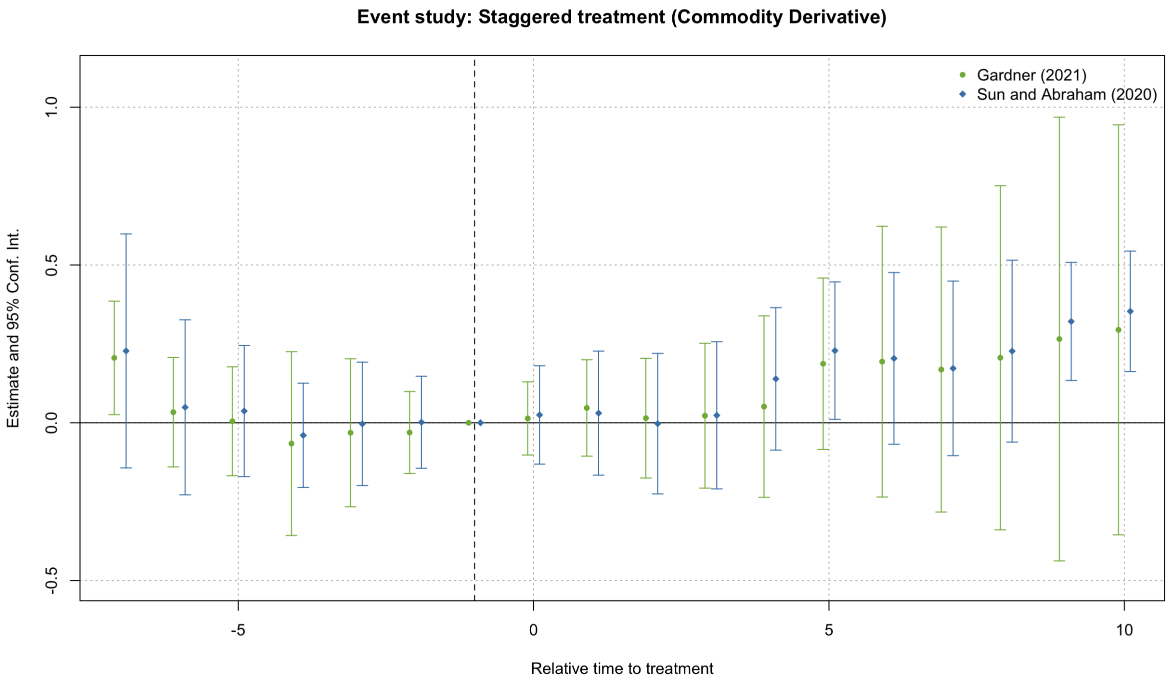

Figure 5.4: Difference-in-Difference event study on Commodity Derivatives

The dynamic difference-in-difference model shows no significant differences between the treatment and control groups six years before treatment. However, there are statistically significant positive coefficients at the 95% confidence level in Year 5, Year 9, and Year 10 according to the Sun & Abraham (2020) estimator, indicating a positive impact of the treatment on firm value.

Figure 5.4 illustrates the parallel trend analysis. Before treatment, there is minimal difference between the treatment and control firms over the six years, as indicated by the Sun & Abraham (2020) estimator. After the treatment, changes increase for both groups, consistently showing positive coefficients. In the post-treatment period, changes exhibit larger fluctuations with several significant effects. This suggests that the usage of commodity derivatives potentially positively impacts Ln(Tobin's Q). The Gardner (2021) and Sun & Abraham (2020) estimators support this conclusion, indicating that the positive effect becomes more pronounced with longer-term usage of commodity derivatives. This can be attributed to the fact that certain firms in Norway rely on export economies and are exposed to commodity price fluctuations, making commodity derivatives more effective when implemented.

Table 5.16, focusing on the years around Year -1 due to space limitations, reveals that one year before and after implementing commodity derivatives exhibit insignificant coefficients near zero across all three models. However, after five years, commodity derivatives have a significant positive effect on Ln(Tobin's Q). The coefficient of the average treatment effect for the treated (ATT) is insignificantly positive, suggesting that the treatment effect is not obvious but potentially positive. Examining the control variables in Model (2), we find that firm size (lSize) and ROA are significant. In terms of interpretation, when firms utilize commodity derivatives to hedge floating commodity price exposures, firm size, and ROA play a significant role in determining firm value. Smaller firm sizes and a lower proportion of sales are associated with potential value creation. This may be attributed to the fact that larger firms' sales and currency values are highly influenced by commodity price volatility, which is particularly relevant for Norwegian firms due to the reliance on exports.

Therefore, the insights we observe are that investment in commodity derivatives could help firms perform more efficiently, but the average effect is not significant. The impact of commodity price fluctuations on a firm's financial performance may not be immediate, and it may take some time for the effects of commodity derivatives to reflect in the firm's financial results.

Table 5.16: DiD Event study: Staggered treatment (Commodity Derivative)

This table shows the impact of Commodity Derivative on firm value for the sample with exposure to commodity price exposure only. Difference-in-Difference event study is applied to this sample using Ln(Tobin's Q) as dependent variable with firm-specific factors as covariates combining with company and time fixed effects. Covariates include Leverage Ratio, Firm Size, Return on Assets, Liquidity Ratio, Current Ratio and Tangibility. The sample includes 90 unique firms, listed in Oslo Stock Exchange, and comprises 949 yearly observations, from year 2007 to 2021. Coefficients and robust standard errors are reported using different estimators. Model (1) is estimated by Gardner (2021), Model (2) is estimated by Sun and Abraham (2020) and Model (3) is estimated by Two-way fixed effects.

Dependent Variable:		Ln(Tobin's Q)	
Model:	(1)	(2)	(3)
Lev	0.0365	0.2168	0.2650
	(0.0509)	(0.1793)	(0.1639)
lSize	0.0020	**-0.0913***	**-0.0777***
	(0.0044)	(0.0526)	(0.0459)
ROA	0.0025	**-0.0442*****	**-0.0440*****
	(0.0026)	(0.0059)	(0.0062)
Liq	-0.0003	0.0021	0.0023
	(0.0002)	(0.0084)	(0.0080)
Curr	0.0003	-0.0034	-0.0036
	(0.0002)	(0.0088)	(0.0083)
Tangibility	**-0.0819***	-0.2504	**-0.3263***
	(0.0422)	(0.2066)	(0.1825)
Year = -2	-0.0308	0.0016	-0.0239
	(0.0663)	(0.0744)	(0.1260)
Year = 0	0.0137	0.0248	0.0408
	(0.0592)	(0.0795)	(0.0829)
Year = 1	0.0471	0.0305	0.0767
	(0.0780)	(0.1003)	(0.1058)
Year = 2	0.0147	-0.0027	0.0532
	(0.0967)	(0.1136)	(0.1031)
Year = 3	0.0223	0.0236	0.0517
	(0.1171)	(0.1190)	(0.0931)
Year = 4	0.0512	0.1391	0.1241
	(0.1467)	(0.1152)	(0.1379)
Year = 5	0.1871	**0.2285****	**0.2558****
	(0.1385)	(0.1112)	(0.1233)
ATT		0.1049	
		(0.0936)	
Fixed-effects			
Company	No	Yes	Yes
Year	No	Yes	Yes
Fit statistics			
Observations	949	949	949
R^2	0.03	0.75	0.70
Within R^2		0.28	0.16

standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.4.5 Placebo Test

A possible concern with our results is the potential presence of differential trends before the first derivative implementation, which may have led to incorrectly attributing these trends to the derivative usage. To address this concern, we thoroughly assessed the parallel trend assumption by visually inspecting the data for each type of derivative. Additionally, we performed placebo tests using data from the period preceding the firm's initial implementation of derivatives, as presented in Table 5.17.

In the first scenario, we set the artificial implementation year of the hedge policy one year earlier for the experimental group. Model (1) for each type of derivative yielded non-significant coefficients for Year 0 and Average Treatment Effect on the Treated (ATT). These results indicate that the parallel trend assumption is satisfied, enhancing our conclusions' robustness.

Similarly, in the second scenario, we set the artificial implementation year of the hedge policy two years earlier for the experimental group. Model (2) for each derivative exhibited non-significant coefficients for Year 0, Year 1, and ATT. This finding further confirms the satisfaction of the parallel trend assumption and reinforces the robustness of our conclusions.

Based on the outcomes of this placebo test, we have reasonably established the robustness of our previous conclusions and successfully verified **Hypothesis 2**. By addressing the concern of differential trends, we provide stronger evidence for the impact of derivative usage on firm value.

Table 5.17: DiD Event study: Staggered treatment (Placebo Test)

This table presents the impact of different types of derivatives on firm value for a sample of firms exposed to floating interest rates, currency fluctuations, or commodity price changes prior to implementing derivatives. We employ a Difference-in-Difference event study approach, using Ln(Tobin's Q) as the dependent variable, while accounting for firm-specific factors and incorporating fixed effects for both companies and time. The covariates considered in the analysis include the Leverage Ratio, Firm Size, Return on Assets, Liquidity Ratio, Current Ratio, and Tangibility. To assess the validity of our findings, we apply a placebo cutoff of one year before the first implementation in Model (1), and a placebo cutoff of two years before the first implementation in Model (2). The coefficients and robust standard errors are estimated based on the methodology introduced by Sun and Abraham (2020).

Target Derivative:	Any		Interest Rate		Currency		Commodity	
Model:	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Lev	0.0512	0.0578	**0.3596***	**0.3815****	0.0973	0.1003	0.1810	0.1888
	(0.1139)	(0.1169)	(0.1868)	(0.1829)	(0.1244)	(0.1259)	(0.1759)	(0.1766)
lSize	**-0.2304*****	**-0.2438*****	-0.0474	-0.0482	**-0.2222*****	**-0.2235*****	-0.0811	-0.0842
	(0.0534)	(0.0516)	(0.0487)	(0.0491)	(0.0398)	(0.0416)	(0.0575)	(0.0580)
ROA	**-0.0481*****	**-0.0475*****	-0.0088	0.0110	**-0.0323*****	**-0.0331*****	**-0.0436*****	**-0.0432*****
	(0.0113)	(0.0117)	(0.0789)	(0.0856)	(0.0080)	(0.0079)	(0.0056)	(0.0056)
Liq	0.0038	0.0037	0.0065	0.0084	**0.0139****	**0.0137****	0.0022	0.0022
	(0.0080)	(0.0079)	(0.0094)	(0.0103)	(0.0057)	(0.0056)	(0.0081)	(0.0081)
Curr	-0.0049	-0.0047	-0.0058	**-0.0065***	**-0.0153****	**-0.0150****	-0.0036	-0.0035
	(0.0083)	(0.0082)	(0.0036)	(0.0038)	(0.0060)	(0.0059)	(0.0085)	(0.0084)
Tangibility	0.0441	0.0712	-0.1419	-0.1868	-0.1558	-0.1462	-0.3303	-0.3296
	(0.3519)	(0.3875)	(0.2628)	(0.2742)	(0.2749)	(0.2776)	(0.2114)	(0.2162)
Year = 0	0.0596	0.0010	0.0169	0.0526	0.0496	-0.0324	0.0134	0.0563
	(0.0740)	(0.0727)	(0.0267)	(0.0618)	(0.0514)	(0.0651)	(0.0738)	(0.0424)
Year = 1		0.0201		-0.0328		0.0028		0.0732
		(0.0911)		(0.0678)		(0.0551)		(0.0957)
ATT	0.0451	-0.0102	0.0169	0.0099	0.0496	-0.0139	0.0134	0.0652
	(0.0788)	(0.0750)	(0.0267)	(0.0608)	(0.0514)	(0.0548)	(0.0738)	(0.0633)
Fixed-effects								
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	638	637	563	559	812	812	809	809
R^2	0.83	0.82	0.86	0.85	0.82	0.82	0.74	0.73
Within R^2	0.34	0.33	0.23	0.22	0.33	0.33	0.22	0.21

standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion

6.1 Empirical Contributions

So far, in the analysis section, we have tested the hypotheses that different types of derivatives have positive relationships with firm value for Norwegian non-financial firms when used accordingly to the relevant exposure for the period of 2007–2021, which encompasses the global financial crisis and the COVID-19 recession. These findings differ from previous work and contribute to the empirical literature, as outlined below.

The primary empirical contribution of this paper is to learn the relationship between derivative usage and firm value from diverse perspectives. In particular, we apply quantile regression models to analyze how derivative usage relates to firm value across its distribution and for different time intervals. Overall, derivative usage positively correlates with firm value, with varying significance across different types of derivatives. Specifically, interest rate and commodity options show significant positive relationships with firm value, while currency options exhibit a negative and insignificant relationship. Both interest rate and currency swaps have significant positive associations with firm value, while interest rate caps show a significant negative relationship. These findings emphasize the importance of considering specific derivative instruments when examining their impact on firm value. Across different time intervals, our analysis reveals varying associations between derivative usage and firm value. From 2010 to 2012, derivative usage is negatively associated with firm value. Specifically, interest rate derivatives exhibit a significant positive relationship only in 2007-2009, while currency derivatives show a significant negative relationship exclusively in 2010-2012. Interestingly, commodity derivatives exhibited a significant positive relationship in 2016-2018, but a significant negative relationship in 2019-2021. These findings highlight the dynamic relationship between derivative usage and firm value, suggesting that the impact can vary across different periods and types of derivatives.

The other empirical contribution is to learn the effect of derivative usage on firm value by implementing a designed difference-in-difference model. We find that derivative users potentially get lagged rewards after the derivatives' first implementation. However, the effects vary depending on the type of derivatives. In general, derivative users will see positive lagged effects and there should be no significant difference across firms; interest rate derivative users, when exposed to floating interest rate risks, will have no strong rewards after their first implementation of the derivatives, and there will be a greater impact on firms with lower firm value; currency derivative users, when exposed to floating foreign exchange rate risks, will have significant positive effects on firm value growth at least four years after their first derivative implementation, and there is no difference between firms with different firm values; commodity derivative users, when exposed to floating commodity price risks, also get evident positive rewards by their increase in firm value at least five years after their first implementation of derivatives. A firm with a lower firm value will see greater effects than one with a higher firm value. These findings cater to the study conducted by Bachiller, Boubaker, & Mefteh-Wali (2021), who mentioned that the usage of derivatives has a varying positive effect on firm value depending on the type of derivatives. Meanwhile, this paper underlines the importance of non-financial firms' incentives in implementing value-enhancing derivatives.

6.2 Managerial Implications

Our paper provides some meaningful, practical implications for firm management activities. The finding that firms using derivatives are more valuable for firms with lower firm value, and the value effects being lagged, provides practical and useful insights for managers to help them adjust their management strategies by implementing derivatives according to their current exposure. It is also more appealing for firms to use currency and commodity derivatives when they have relevant risks. Therefore, firm managers should measure their current risk exposure and be patient after their first implementation of derivatives.

Meanwhile, this paper suggests that regulators or policymakers in Norway might have practical reasons to incentivize non-financial firms to perform hedging of financial and operational exposures, especially to obtain improved debt financing, currency exchange, and commodity transactions. Also, the findings potentially reveal that Norwegian firms are largely exposed to floating foreign exchange exposure and commodity prices, as their hedges actually affect them.

6.3 Limitations and Future Research

Despite the significant findings and contributions above, this study has the following limitations:

First, we estimate the value effects of derivative usage using a dummy variable, but we do not consider the degree to which the firms hedge their corresponding exposure. The firms are not required to reveal this information in their annual reports, but it would still be interesting to introduce hedge efficiency in our models. Moreover, the floating interest rate, foreign exchange, and commodity price exposure are also estimated using dummy variables. However, the motivation to implement derivatives also depends on the extent to how exposed the firms are. Again, the firms do not directly reveal the specific amount of exposure they have in their annual reports. Thus, future research would benefit from more precise information on these aspects.

Second, while the designed difference-in-difference helps us explore the relationship between derivatives and firm value growth, the estimate asks to drop the samples without non-treatment time, potentially making the estimate biased. This means that some of the firms that consistently used derivatives from 2007 to 2021 will be omitted because they have a post-treatment period only. Thus, future research might cover a broader range of samples in a wider period, which could better explore the value effect of derivative usage.

Lastly, while exploring the possibilities of instrumental variable estimations as another measure of robustness, we failed to identify any relevant instruments applicable to derivative usage in the dataset. Further exploration into this issue could strengthen the analysis and results obtained.

References

Allayannis, G., Lel, U., and Miller, D. P. (2012). The use of foreign currency derivatives, corporate governance, and firm value around the world. *Journal of International Economics*, 87(1):65–79.

Allayannis, G. and Weston, J. P. (2001). The use of foreign currency derivatives and firm market value. *The Review of Financial Studies*, 14(1):243–276.

Arilyn, E. J. (2020). The influence of profitability, asset tangibility, firm size, liquidity, and agency conflict toward capital structure on food and beverage companies listed in indonesia stock exchange. *Journal of Emerging Economies and Islamic Research*, 8(1):23–30.

Bachiller, P., Boubaker, S., and Mefteh-Wali, S. (2021). Financial derivatives and firm value: What have we learned? *Finance Research Letters*, 39:101573.

Bartram, S. M., Brown, G. W., and Conrad, J. (2011). The effects of derivatives on firm risk and value. *Journal of Financial and Quantitative Analysis*, 46(4):967–999.

Belghitar, Y., Clark, E., and Mefteh, S. (2013). Foreign currency derivative use and shareholder value. *International Review of Financial Analysis*, 29:283–293.

Campa, J. M. and Kedia, S. (2002). Explaining the diversification discount. *The Journal of Finance*, 57(4):1731–1762.

Chen, J.-L. and King, T.-H. D. (2014). Corporate hedging and the cost of debt. *Journal of Corporate Finance*, 29:221–245.

Clark, E. and Judge, A. (2009). Foreign currency derivatives versus foreign currency debt and the hedging premium. *European Financial Management*, 15(3):606–642.

Clark, E. and Mefteh, S. (2010). Foreign currency derivatives use, firm value and the effect of the exposure profile: Evidence from france. *International Journal of Business*, 15(2):183.

Efron, B. (1992). *Bootstrap Methods: Another Look at the Jackknife*, pages 569–593. Springer New York.

Farhan, N. H., Alhomidi, E., Almaqtari, F. A., and Tabash, M. I. (2019). Does corporate governance moderate the relationship between liquidity ratios and financial performance? evidence from indian pharmaceutical companies. *Academic Journal of Interdisciplinary Studies*, 8(3):144–144.

Fauver, L. and Naranjo, A. (2010). Derivative usage and firm value: The influence of agency costs and monitoring problems. *Journal of Corporate Finance*, 16(5):719–735.

Gardner, J. (2022). Two-stage differences in differences. *arXiv preprint*.

Graham, J. R. and Smith, C. W. (1999). Tax incentives to hedge. *The Journal of Finance*, 54(6):2241–2262.

Guay, W. R. (1999). The impact of derivatives on firm risk: An empirical examination of new derivative users. *Journal of Accounting and Economics*, 26(1-3):319–351.

Hagelin, N. and Pramborg, B. (2004). Hedging foreign exchange exposure: Risk reduction from transaction and translation hedging. *Journal of International Financial Management & Accounting*, 15(1):1–20.

Helland, F. and Bjerkelund, S. (2016). Currency hedging in the norwegian seafood industry. Master's thesis, University of Stavanger, Norway.

Husna, A. and Satria, I. (2019). Effects of return on asset, debt to asset ratio, current ratio, firm size, and dividend payout ratio on firm value. *International Journal of Economics and Financial Issues*, 9(5):50–54.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, 76(2):323–329.

Jin, Y. and Jorion, P. (2006). Firm value and hedging: Evidence from us oil and gas producers. *The Journal of Finance*, 61(2):893–919.

Kim, H. T., Papanastassiou, M., and Nguyen, Q. (2017). Multinationals and the impact of corruption on financial derivatives use and firm value: Evidence from east asia. *Journal of Multinational Financial Management*, 39:39–59.

Koenker, R. (2004). Quantile regression for longitudinal data. *Journal of Multivariate Analysis*, 91(1):74–89.

Lookman, A. A. (2004). Does hedging increase firm value? comparing premia for hedging 'big' versus 'small' risks. *EFA*.

Machado, J. A. and Silva, J. S. (2019). Quantiles via moments. *Journal of Econometrics*, 213(1):145–173.

Magee, S. (2013). Foreign currency hedging and firm value: A dynamic panel approach. In *Palgrave Macmillan UK*, pages 57–80.

Modigliani, F. and Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review*, 48(3):261–297.

Panaretou, A. (2014). Corporate risk management and firm value: Evidence from the uk market. *The European Journal of Finance*, 20(12):1161–1186.

Santos, R. B. d., Lima, F. G., Gatsios, R. C., and de Almeida, R. B. (2017). Risk management and value creation: New evidence for brazilian non-financial companies. *Applied Economics*, 49(58):5815–5827.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Ullah, S., Irfan, M., Kim, J. R., and Ullah, F. (2021). Capital expenditures, corporate hedging and firm value. *The Quarterly Review of Economics and Finance*.

Uribe, J. M. and Guillen, M. (2020). *Quantile Regression for Cross-Sectional and Time Series Data: Applications in Energy Markets Using R*. Springer International Publishing, Cham, Switzerland.

Xue, Q., Wang, Z., Liu, S., and Chang, P. (2022). Hedging, vertical integration and firm value: Evidence from the oil and gas industry. *Fuel*, 310:122349.

Appendix

A1 Table of Variables

Table A1.1: Variables Used

Definitions of dependent-, independent-, and control variables. Subscripts BV and MV are shorthand notation for book value and market value, respectively.

Variable	Definition
Dependent variables	
Ln(Tobin's Q)	$\log(\frac{Assets_{BV} - Equity_{BV} + Equity_{MV}}{Assets_{BV}})$
Independent variables	
Derivative Usage	1 for firms using derivatives; 0 otherwise.
Derivative Types	
Interest Rate Derivatives	1 for firms using interest rate derivatives; 0 otherwise.
Foreign Exchange Derivatives	1 for firms using currency derivatives; 0 otherwise.
Commodity Derivatives	1 for firms using commodity derivatives; 0 otherwise.
Derivative Instruments	
Forward Derivatives	1 for firms using forward derivative instruments; 0 otherwise.
Options Derivatives	1 for firms using option derivative instruments; 0 otherwise.
Swaps Derivatives	1 for firms using swap derivative instruments; 0 otherwise.
Caps Derivatives	1 for firms using interest rate caps instruments; 0 otherwise.
Control variables	
Return on Assets	$\frac{Net\ Income}{Assets_{BV}}$
Leverage	$\frac{Liabilities_{BV}}{Assets_{BV}}$
Current Ratio	$\frac{Current\ Assets_{BV}}{Current\ Liabilities_{BV}}$
Liquidity	$\frac{Cash\ and\ Cash\ Equivalents_{BV}}{Current\ Liabilities_{BV}}$
Tangibility	$\frac{Net\ Property, Plants\ and\ Equipments_{BV}}{Assets_{BV}}$
Firm Size	$\log(Assets_{BV})$
Industry	Factor-dummy set to each type of industry
Risk Exposure	
Any Risk Exposure	1 for firms exposed to floating interest rates, foreign currency, or commodity prices; 0 otherwise.
Floating Interest Rate Exposure	1 for firms exposed to floating interest rates; 0 otherwise.
Foreign Exchange Exposure	1 for firms exposed to foreign currency; 0 otherwise.
Commodity price Exposure	1 for firms exposed to floating commodity prices; 0 otherwise.

A2 List of Commodities

- Bitumen
- Crude oil
- Natural gas
- Coal
- Hydrogen
- Biofuel
- Electricity/energy for power-intensive industrial firms
- Bunker fuel for shipping
- Aviation jet fuel
- Salmon
- Silicon
- Steel
- Rubber and plastic made from, among others, styrene and propene
- Copper
- Zinc
- Aluminium
- Wood
- Agricultural products in general
- Other raw minerals from mining operations, like gold and silver

A3 Data-Set Plots

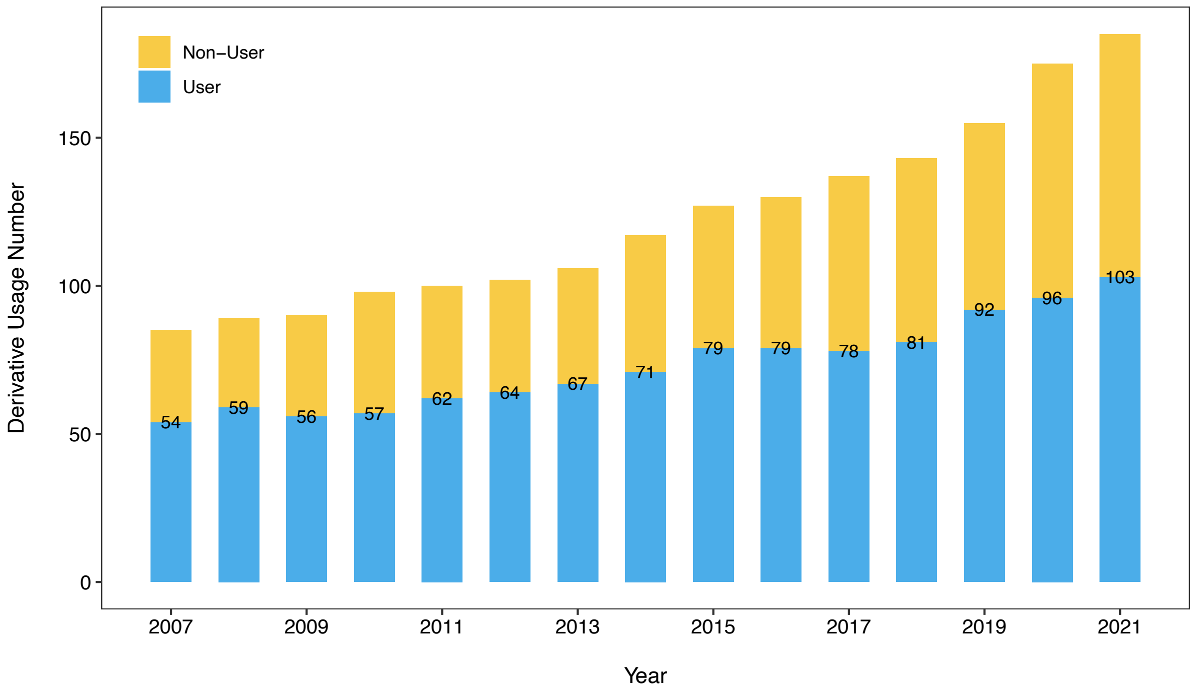

Figure A3.1: Use of derivatives, by users and non-users, 2007–2021

The figure shows the unconditional yearly distribution of derivative usage. Categories include derivative users and derivative non-users.

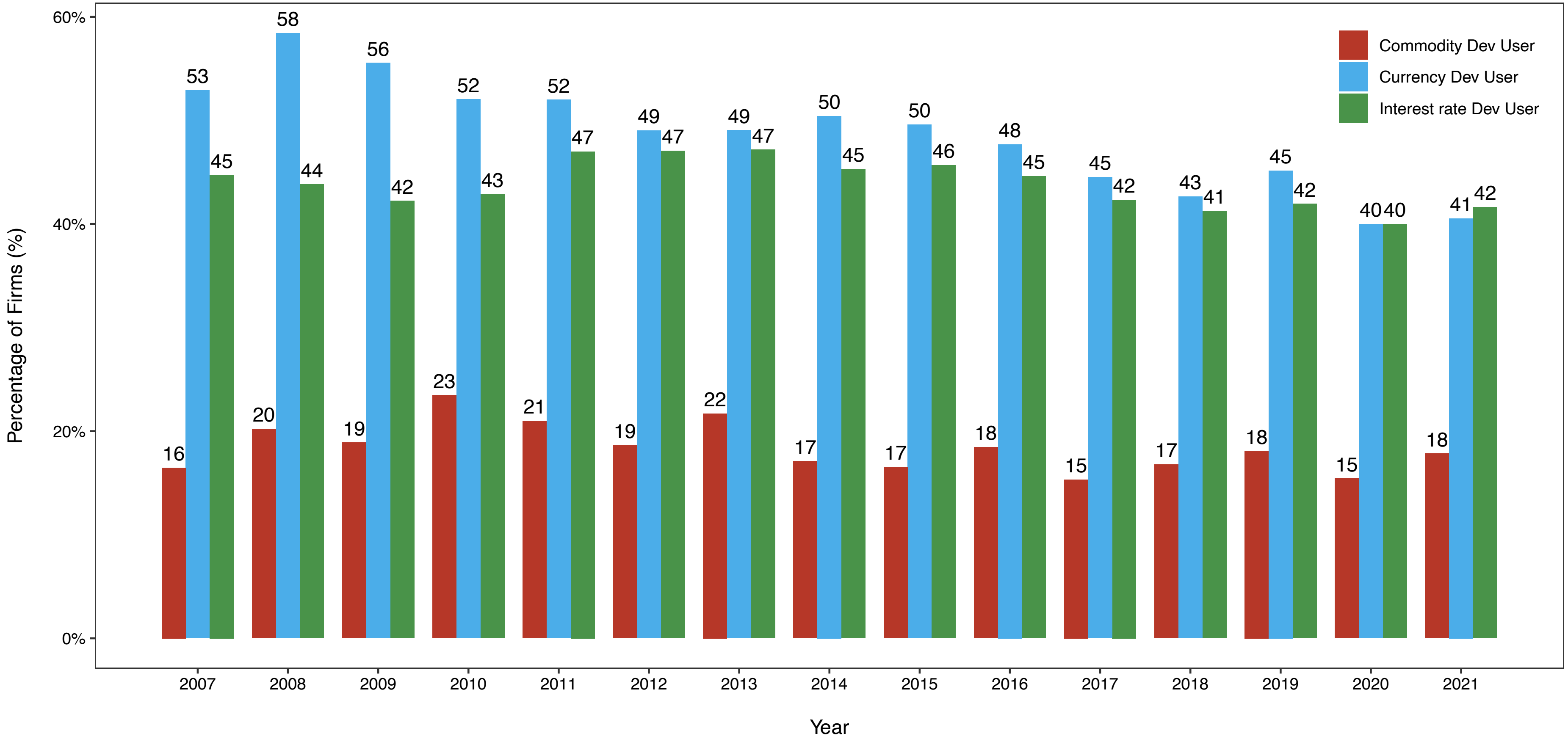

Figure A3.2: Use of derivatives, by types, 2007–2021

The figure shows the unconditional yearly distribution of derivative types usage. Categories include interest rate derivatives (forward, options, swaps and caps), currency derivatives (forward, options, and swaps), commodity derivatives (forward, options, and swaps).

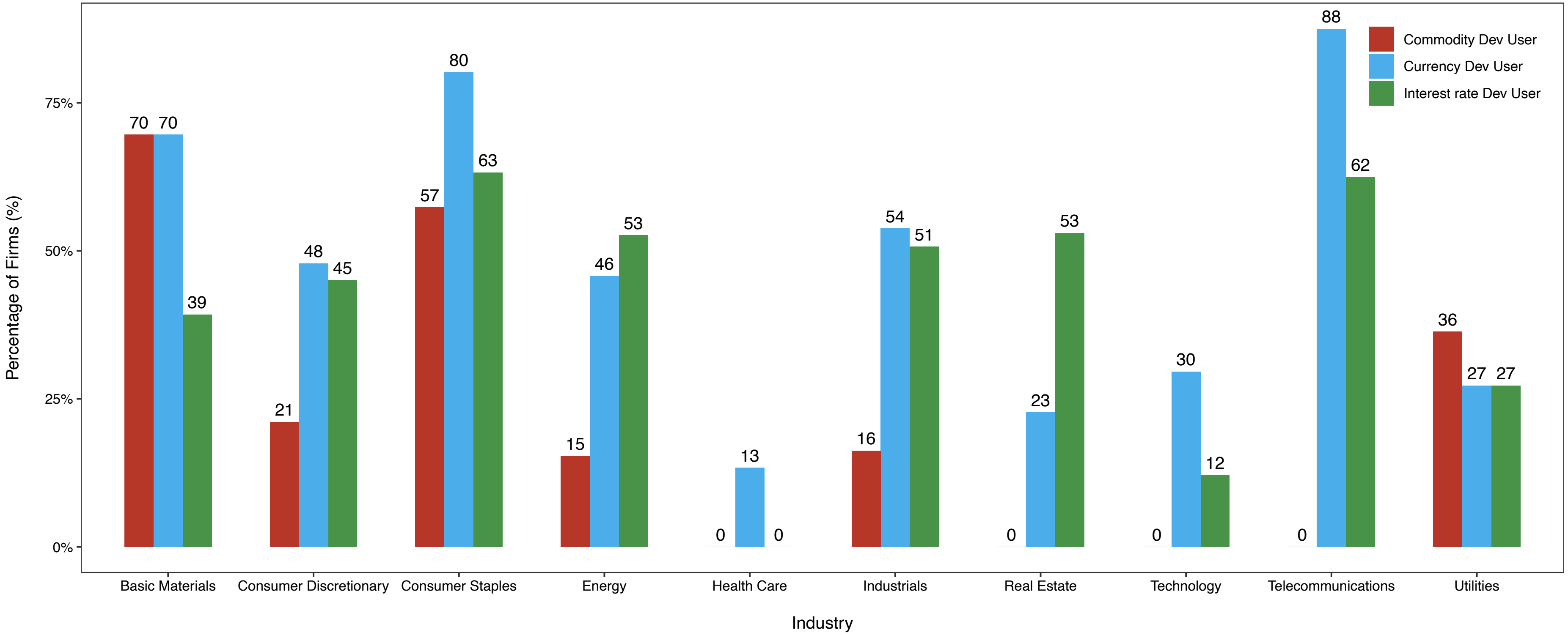

Figure A3.3: Use of derivatives (types), by Industry, 2007–2021

The figure shows the unconditional distribution of derivative types usage for various industries. Categories include interest rate derivatives (forward, options, swaps and caps), currency derivatives (forward, options, and swaps), commodity derivatives (forward, options, and swaps).

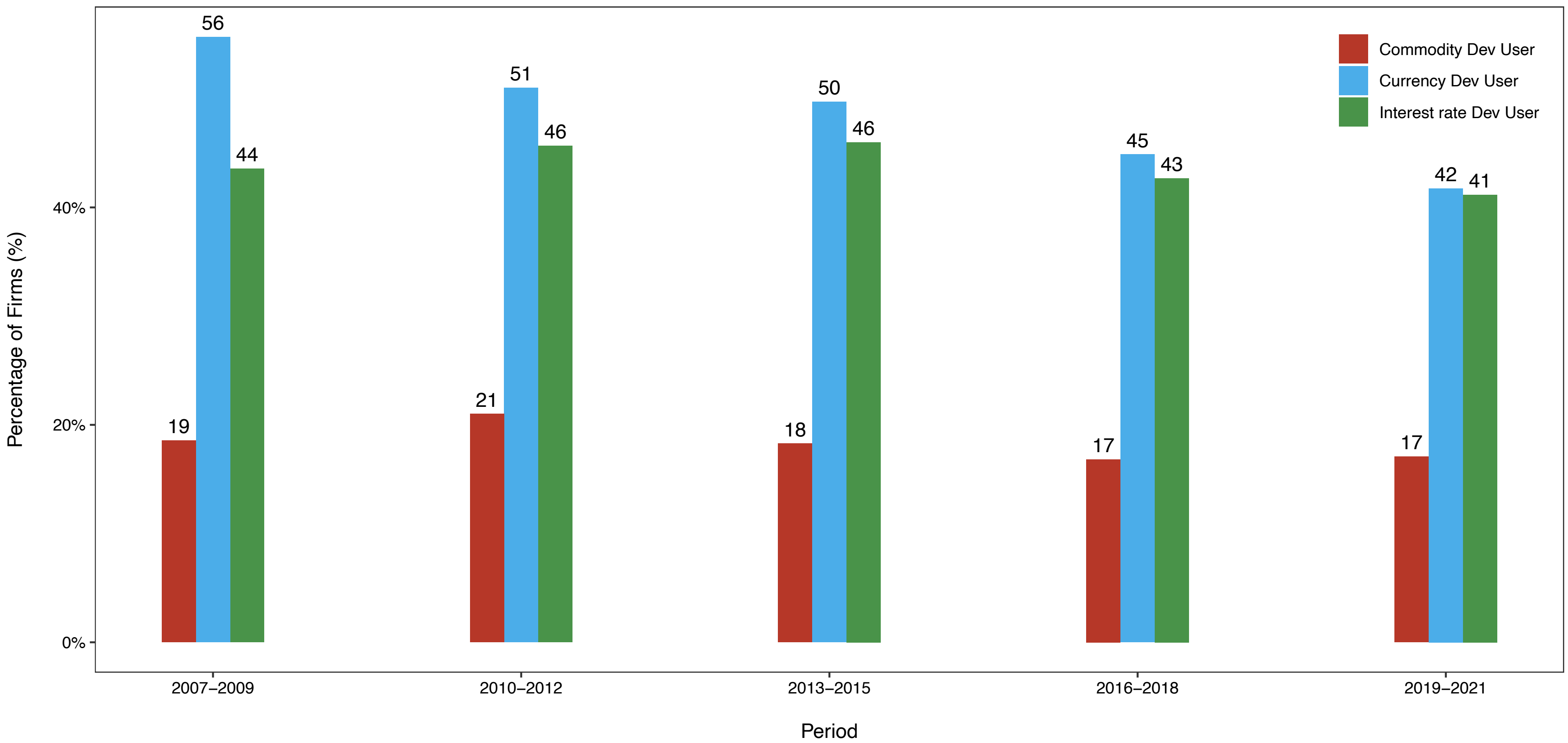

Figure A3.4: Use of derivatives (types), by period, 2007–2021

The figure shows the unconditional periodical distribution of derivative types usage. Categories include interest rate derivatives (forward, options, swaps and caps), currency derivatives (forward, options, and swaps), commodity derivatives (forward, options, and swaps).

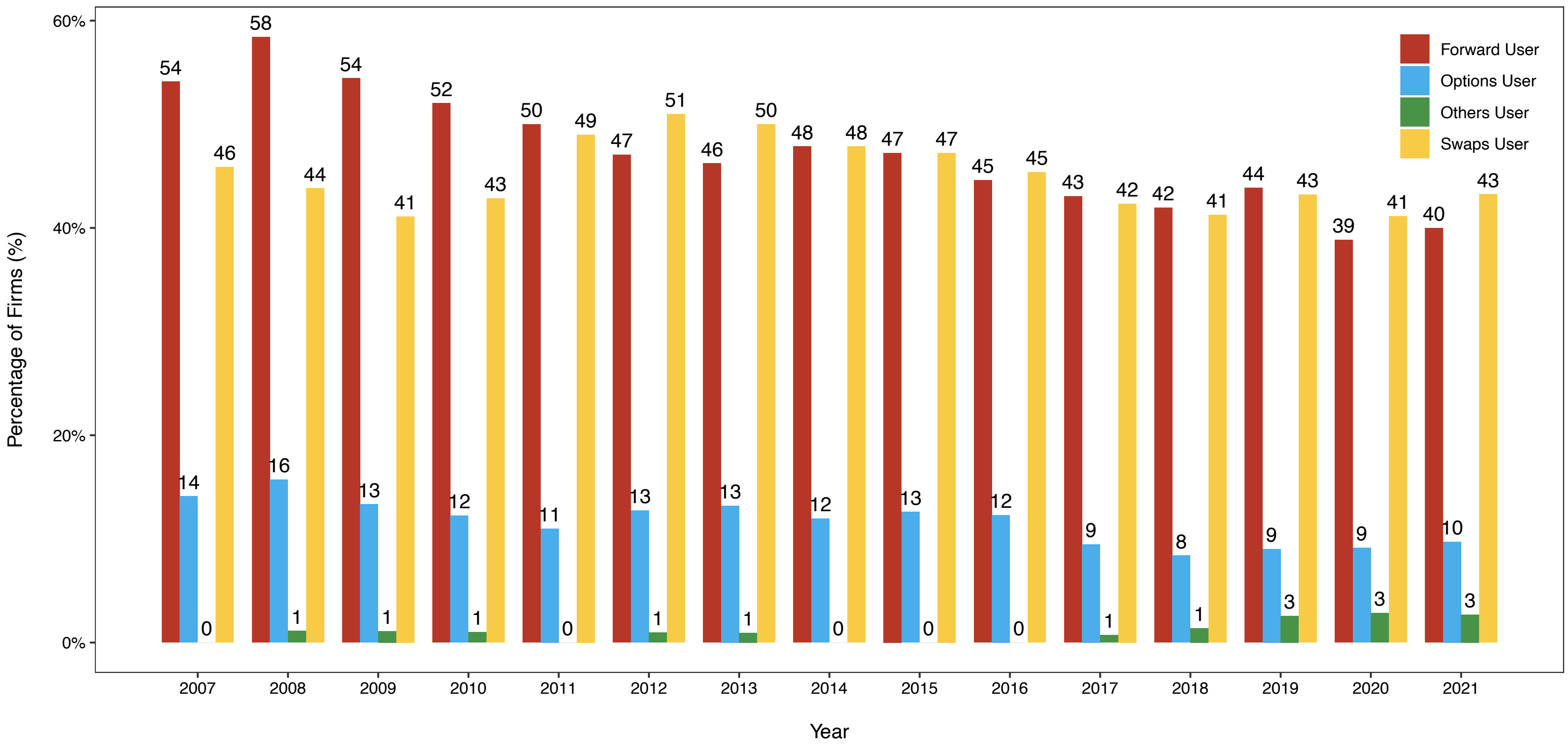

Figure A3.5: Use of derivatives, by instruments, 2007–2021

The figure shows the unconditional yearly distribution of derivative types usage. Categories include forwards (including forward rate agreements, currency, and commodity), options (interest rate, currency, and commodity), swaps (interest rate, currency, and commodity), and others (mainly interest rate caps).

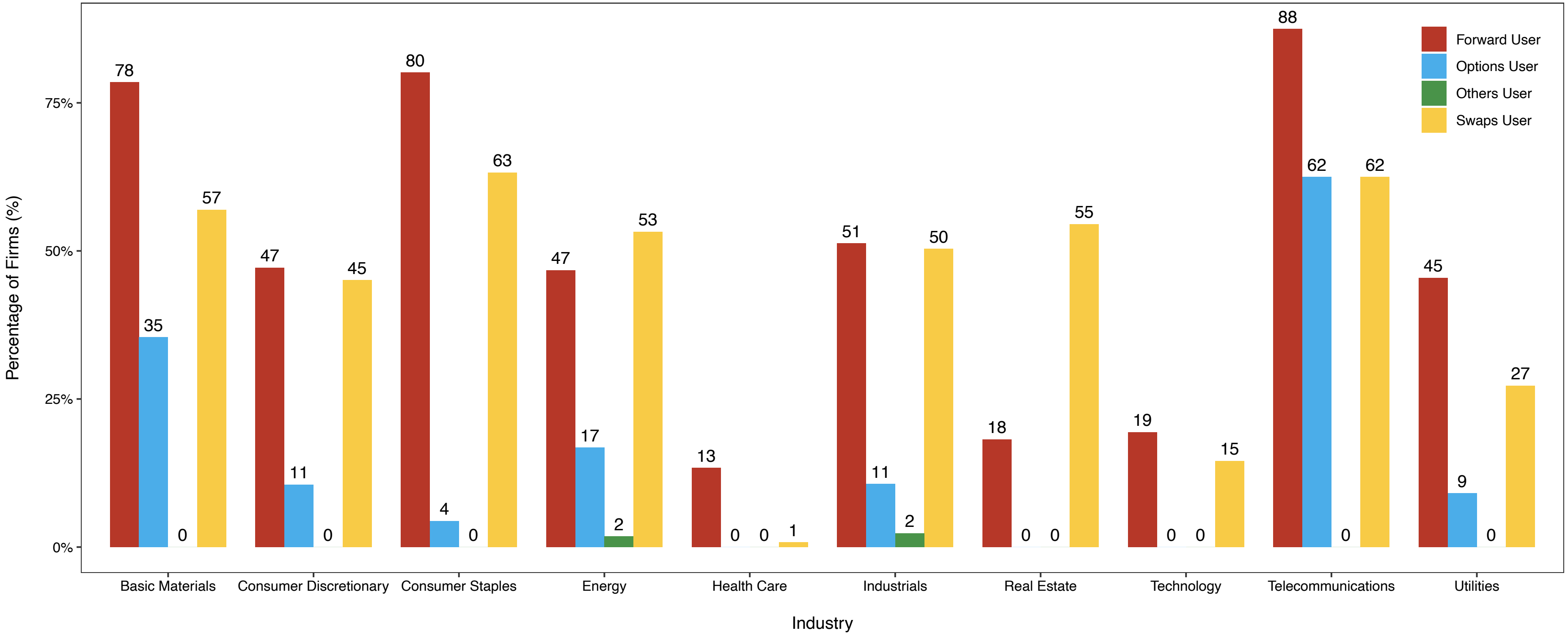

Figure A3.6: Use of derivatives (instruments), by industry, 2007–2021

The figure shows the unconditional distribution of derivative instrument usage for various industries. Categories include forwards (including forward rate agreements, currency, and commodity), options (interest rate, currency, and commodity), swaps (interest rate, currency, and commodity), and others (mainly interest rate caps).

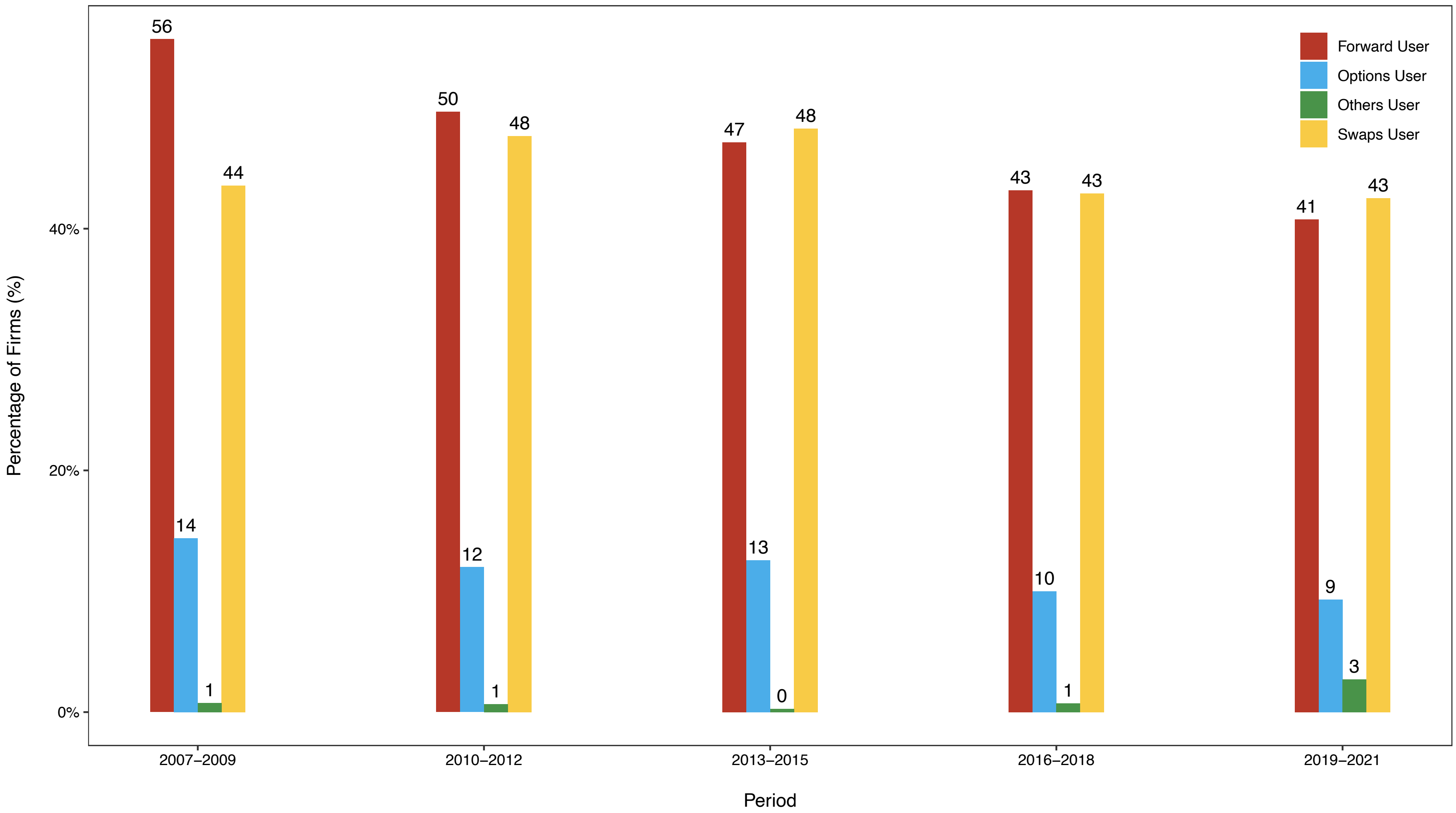

Figure A3.7: Use of derivatives (instruments), by period, 2007–2021

The figure shows the unconditional periodical distribution of derivative instrument usage. Categories include forwards (including forward rate agreements, currency, and commodity), options (interest rate, currency, and commodity), swaps (interest rate, currency, and commodity), and others (mainly interest rate caps).

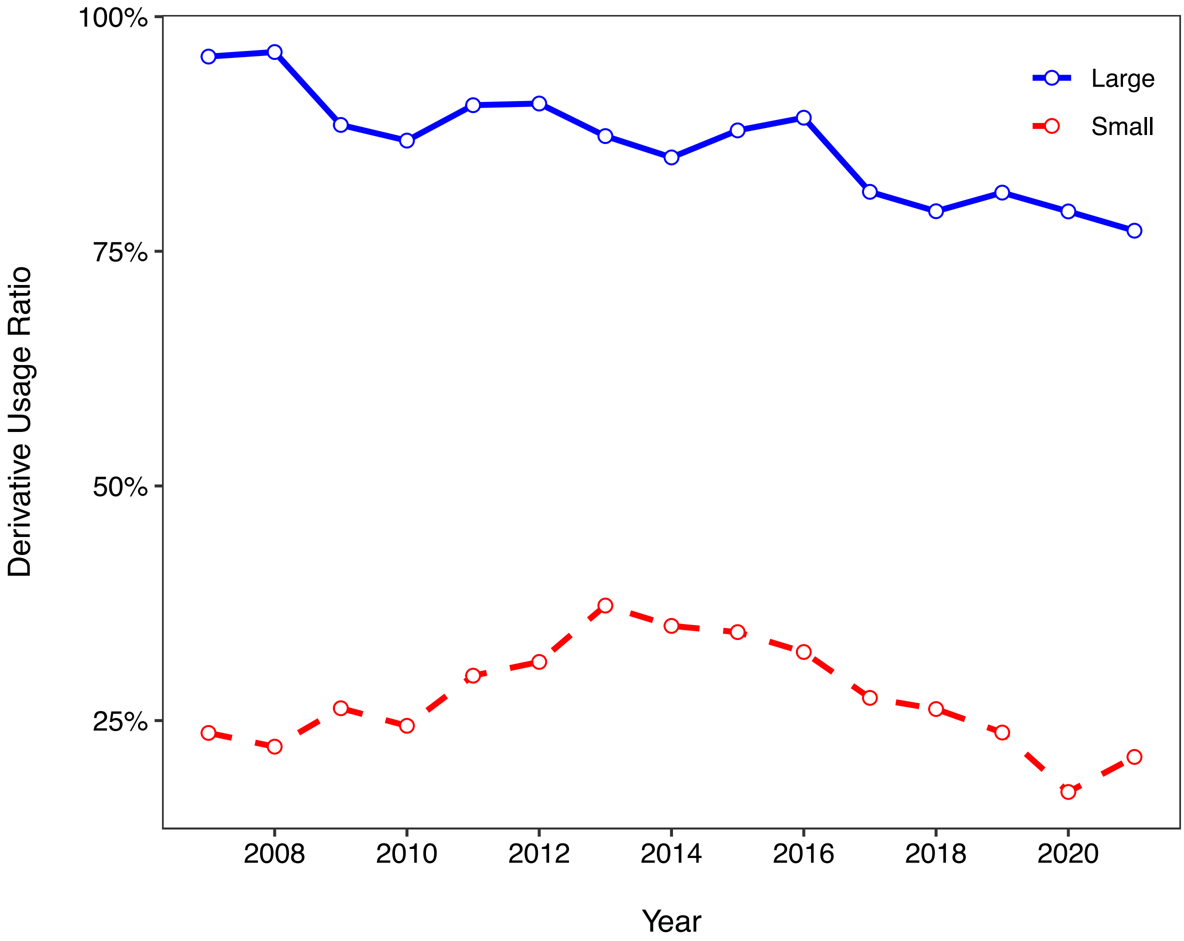

Figure A3.8: Use of derivatives (types), by firm size, 2007–2021

The figure shows the unconditional yearly distribution of derivative usage. Categories include large and small firms, with the median size value as the dividing criterion for each year.

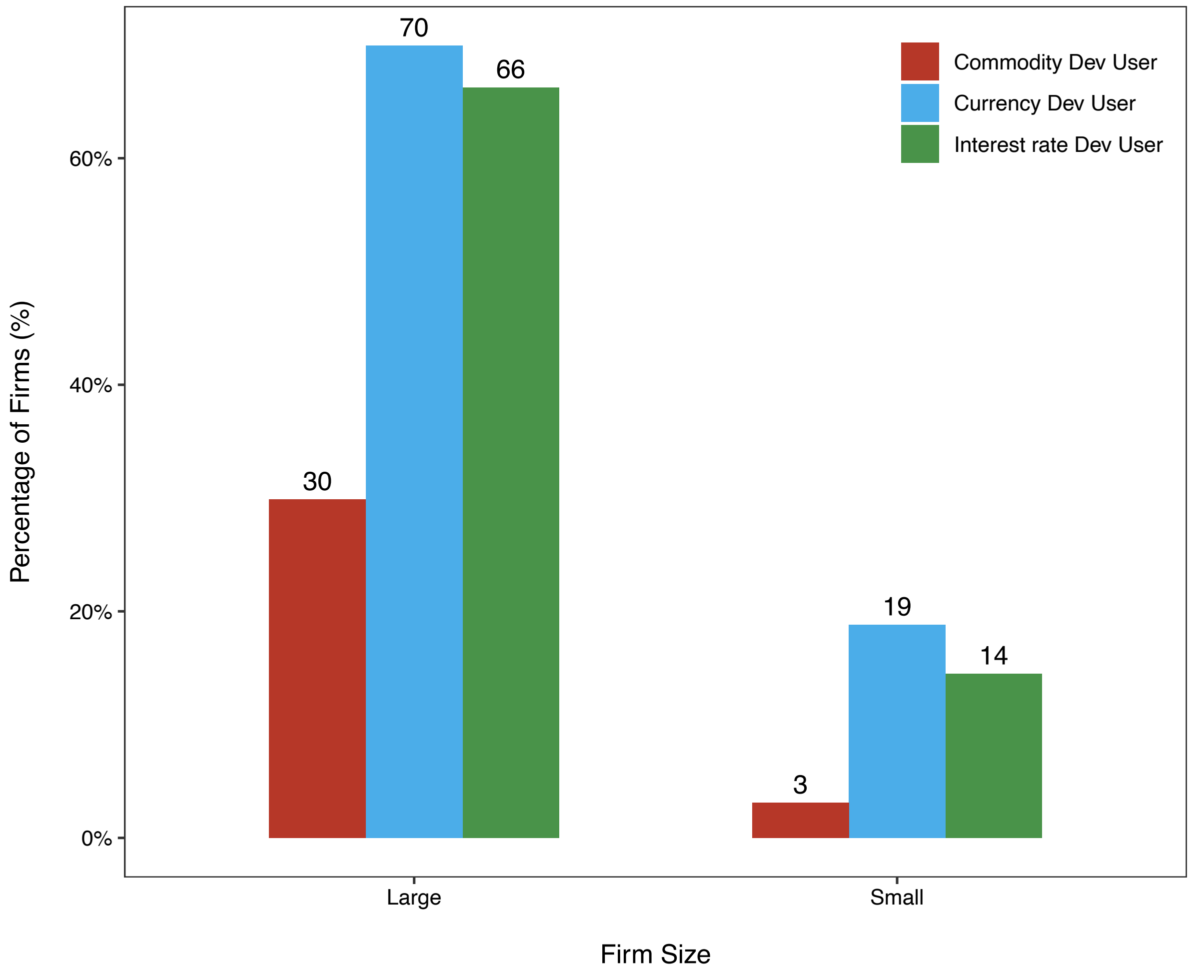

Figure A3.9: Use of derivative (types), by firm size, 2007–2021

The figure shows the unconditional yearly distribution of derivative types usage with the median size value as the dividing criterion for large and small firms. Categories include forwards (including forward rate agreements, currency, and commodity), options (interest rate, currency, and commodity), swaps (interest rate, currency, and commodity), and others (mainly interest rate caps).

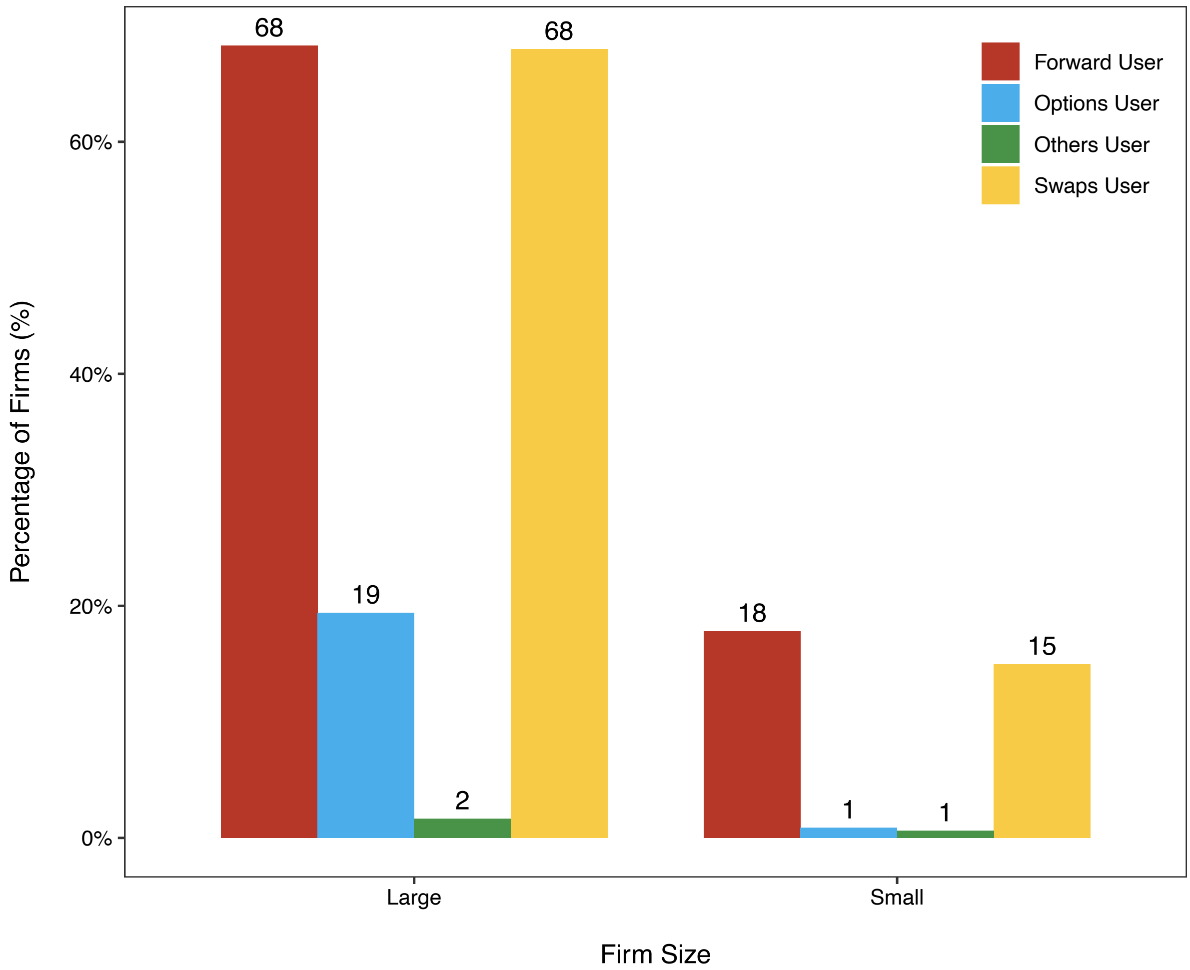

Figure A3.10: Use of derivatives (instruments), by firm size, 2007–2021

The figure shows the unconditional yearly distribution of derivative instrument usage with the median size value as the dividing criterion for large and small firms. Categories include forwards (including forward rate agreements, currency, and commodity), options (interest rate, currency, and commodity), swaps (interest rate, currency, and commodity), and others (mainly interest rate caps).

A4 Code Listings

This appendix contains the R and Stata source code developed for this project.

A4.1 Stata: OLS and Quantile Regression

```
clear

* Change the working directory to where the CSV file is located
cd "/Users/hejun/Desktop/e-books/Python/Python/2022/Master-Thesis_new/Data"

* Import your CSV dataset
import delimited "Data.csv", clear

* Encode the string variable "Company" into a numeric variable "CompanyID"
encode company, gen(_company)

xtset _company year

generate companyid= _company

global xlist "liq curr lev_fin roa size tangibility"

generate exposure = fx_exposure
generate dev = fx_dev

global dep_var "qt"
global devlist "dev"

xtreg $dep_var ///
  $devlist $xlist i.year if exposure == 1, fe vce(cluster companyid)
eststo model_ols
estadd scalar fixed = 1 // 1 represents "yes"

bootstrap, cluster(companyid) idcluster(_company) reps(100) seed(1234): mmqreg $dep_var ///
$devlist $xlist  if exposure == 1, q(5) abs(_company year)
eststo model1
estadd scalar fixed = 1 // 1 represents "yes"

bootstrap, cluster(companyid) idcluster(_company) reps(100) seed(1234): mmqreg $dep_var ///
$devlist $xlist  if exposure == 1, q(10) abs(_company year _industry)
eststo model2
estadd scalar fixed = 1 // 1 represents "yes"

bootstrap, cluster(companyid) idcluster(_company) reps(100) seed(1234): mmqreg $dep_var ///
$devlist $xlist  if exposure == 1, q(25) abs(_company year _industry)
eststo model3
estadd scalar fixed = 1 // 1 represents "yes"

bootstrap, cluster(companyid) idcluster(_company) reps(100) seed(1234): mmqreg $dep_var ///
$devlist $xlist  if exposure == 1, q(50) abs(_company year _industry)
eststo model4
estadd scalar fixed = 1 // 1 represents "yes"

bootstrap, cluster(companyid) idcluster(_company) reps(100) seed(1234): mmqreg $dep_var ///
$devlist $xlist  if exposure == 1, q(75) abs(_company year _industry)
eststo model5
estadd scalar fixed = 1 // 1 represents "yes"

bootstrap, cluster(companyid) idcluster(_company) reps(100) seed(1234): mmqreg $dep_var ///
$devlist $xlist  if exposure == 1, q(90) abs(_company year _industry)
eststo model6
estadd scalar fixed = 1 // 1 represents "yes"

bootstrap, cluster(companyid) idcluster(_company) reps(100) seed(1234): mmqreg $dep_var ///
$devlist $xlist  if exposure == 1, q(95) abs(_company year)
eststo model7
estadd scalar fixed = 1 // 1 represents "yes"
```

```
* Change the working directory to where the CSV file is located
cd "/Users/hejun/Documents/NHH/Paper/NHH/Table"

esttab model_ols model1 model2 model3 model4 model5 model6 model7 using table4.tex, replace ///
    title("Benchmark Regression: Currency Derivatives") ///
  nomtitles ///
    label ///
    varlabels(_cons "") ///
    b(%9.4f) t(%9.2f) star(* 0.10 ** 0.05 *** 0.01) ///
    order( dev liq curr lev_fin roa size tangibility) ///
    keep( dev liq curr lev_fin roa size tangibility) ///
    stats(fixed N r2, labels("Firm fixed effects" "Observations") fmt(%9.0g %9.0g %9.2f)) ///
    mgroups("FE" "q0.05" "q0.10" "q0.25" "q0.50" "q0.75" "q0.90" "q0.95", pattern(1 1 1 1 1 1 1 1)) ///
  indicate("Year dummies = *.year") ///
    nonumbers
```

A4.2 R: Difference-in-Difference: Event Study

```
library(did2s)
library(fixest)
library(broom)
library(stargazer)

# 1 - load our example data
df <- read.csv("./Data/did2s_FX.csv", header=TRUE, sep=",")

policy_period = 10
df$Treat_year = df$Treat_FX_year

# 2 - generate years relative to treatment, never treated units get "Inf"
# we'll use these for the dynamic DiD / event study estimation later
df = df %>%
  mutate(
    rel_year = if_else(is.na(Treat_year) == "TRUE", Inf, Year - Treat_year),
    treat = if_else(rel_year != Inf, if_else(rel_year >= 0, 1, 0), 0),
    Treat_year = ifelse(is.na(Treat_year), Inf, Treat_year),
  ) %>%
  filter(FX_Exposure == 1)


# 3 - Results of Models
# ---Event-study Estimate of Gardner (2021) Model ----------------
es = did2s(
  data = df,
  yname = "QT",
  treatment = "treat",
  first_stage = ~ Lev_fin + Size + ROA + Liq + Curr + Tangibility + factor(Industry) | Company + Year,
  second_stage = ~ Lev_fin + Size + ROA + Liq + Curr + Tangibility +
i(rel_year, ref = c(-1, Inf)),
  cluster_var = "Company",
  verbose = FALSE
)

# ---Event-study Estimate of TWFE Model ----------------

twfe = feols(QT ~ Lev_fin + Size + ROA + Liq + Curr + Tangibility +
i(rel_year, ref=c(-1, Inf)) | Company + Year, data = df)


# ---Event-study Estimate of Sun and Abraham (2020) Model ----------------

df$rel_year = df$Year

sa = feols(QT ~ Lev_fin + Size + ROA + Liq + Curr + Tangibility + factor(Industry) +
sunab(Treat_year, rel_year) | Company + Year,
           cluster = as.formula(paste("~", "Company")),
           data = df)
```

```
summary(sa, agg = "att")


# 4 - Plot with Event-Study
fixest::iplot(list(es, sa), sep = 0.2, ref.line = -0.5, pt.join = FALSE, ci_level = 0.95,
              col = c("#82b446", "steelblue"), pt.pch = c(20, 18),
              xlab = "Relative time to treatment",
              main = "Event study: Staggered treatment (Currency Derivatives)",
              xlim = c(-policy_period+4, policy_period), ylim = c(-.5,1.1), xaxt = "n")

# Add legend
legend("topright", # Position of the legend
       legend = c("Gardner (2021)", "Sun and Abraham (2020)"), # Legend labels
       col = c("#82b446", "steelblue"), # Legend colors
       pch = c(20, 18), # Point symbols
       bty = "n", # No box around the legend
       cex = 1) # Legend text size

# 5 - Output the Plot with Event-Study
png(file=paste("output/","Derivative_Currency.png", sep=""),width=2500, height=1500, res=200)
iplot(list(es, sa), sep = 0.2, ref.line = -1, pt.join = FALSE, ci_level = 0.95,
      col = c("#82b446", "steelblue"), pt.pch = c(20, 18),
      xlab = "Relative time to treatment",
      main = "Event study: Staggered treatment (Currency Derivative)",
      xlim = c(-policy_period+3, policy_period), ylim = c(-.5,1.1), xaxt = "n")

legend("topright", # Position of the legend
       legend = c("Gardner (2021)", "Sun and Abraham (2020)"), # Legend labels
       col = c("#82b446", "steelblue"), # Legend colors
       pch = c(20, 18), # Point symbols
       bty = "n", # No box around the legend
       cex = 1) # Legend text size

dev.off()

# Output the Table with Event-Study
etable(list(es,sa,twfe), tex = TRUE, file = "./output/Derivative_Currency.tex")
```