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Commodity Derivative Usage in U.S. Non-Financial Firms

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COMMODITY DERIVATIVE USAGE IN UNITED STATE NON-FINANCIAL FIRMS

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Chapter 1: Introduction

Financial derivatives have been studied and scrutinized in depth since the financial crises in 2007-2009. Derivatives' effect on firms, in particular firm value, have been studied prior to, during, and post global recession, with no definitive answer as to whether this relationship is positive or negative. The global oil price shock that occurred in 2014 drove our interest in how this commodity, along with other commodities are hedged by companies to mitigate risk, and whether or not this action has a particular effect on firm value. We focus our research on U.S. non-financial firms from the Standard and Poor's 500 Index (S&P 500 Index), and evaluate firm value using Pooled Ordinary Least Squares (Pooled OLS) regressions and fixed effect between 2006-2017. This time period allows us to see the relationship between commodity derivative usage and firms during periods of an economic downturn, as well as during a commodity price shock. By looking at S&P500 Index companies it gives us a better idea of commodity derivative usage on a larger and broader scale.

We find that, firstly with the univariate test the firm value of the users are significantly lower than the firm value of the non-users, proxy by the Tobin's Q. Secondly, with the multivariate test, we use the Fixed Effect estimator to deal the problem because of the biased Pooled OLS estimator. We also found that the distribution of the firms' value with commodity derivatives are less peaked than the distribution of the firms' value without commodity derivatives. It implies that using commodity serves the firm as the insurance.

For the Tobin's Q and the firm size, as the proxies of the firm values, the mean and the median of the user Tobin's Q are statistically significant different to the mean of the non-users.

Chapter 2: Literature Review

2.1 EARLY LITERATURE

Much research and work has been done to build on and refine the corporate finance theory put forth by Modigliani and Miller in 1958. According to their theory, assuming perfect financial markets, a firm should have no need to hedge, since corporate risk management practices would not matter, and therefore shareholders would be indifferent in regard to a firm's choice to hedge. Of course, other authors are quick to point out market imperfections and how these lead to failings within Modigliani and Miller's Corporate Finance Theory.

Offering one of the earliest theoretical research papers devoted to hedging, Stulz (1984) posits a model that value-maximizing firms pursue active hedging policies. Stulz also derives optimal hedging policies for risk-averse agents, given that there is uncertainty in commodity prices, and with the assumption that managers want to maximize their expected lifetime utility. The model is explained using foreign exchange forward contracts, which firms use to mitigate their exchange rate risk, but the methodology and results apply more generally to other types of hedging instruments.

Further examining companies' corporate risk management practices, Smith and Stulz (1985) reason that a firm's value consists of the present value of expected cash flows, minus the present value of expected distress costs. Hedging increases a firm's value as long as hedging can reduce a firm's probability of bankruptcy. One goal of this model was that it could be applied to large, widely held corporations. In particular, ones whose owners, stockholders, and bondholders have the ability to hold diversified portfolios of securities. This sets the scene for further research on hedging effecting firm value for large corporations. They develop a positive theory of hedging by value-maximizing corporations, in which hedging is part of overall corporate financing policies.

Froot, Scharfstein, and Stein (1993) develop a new framework in which to analyze corporate risk management policies. They introduce the possibility of using risk management as a means to finance the firm, believing this could resolve financing issues during a funding constraint. When external financing is more expensive than using internal funds, they argue, firms will hedge. This is because hedging can allow a firm to reduce the need for external financing when investors require a higher return. They argue that without risk management, these firms will be forced to take subpar investments. When funds are low, getting financing is costly, and forces firms to scale back value-maxing investments.

2.2 COMMODITY DERIVATIVE USAGE AND FIRM VALUE

A large amount of previous research into firms' use of commodity derivatives has been focused on two industries; the gold mining industry and the oil and gas industry. The oil and gas industry can be divided into commodity producers and commodity users; one such commodity user that has been extensively studied is the airline industry. These industries have a natural exposure to these commodities, and therefore have an obvious incentive to hedge.

2.2.1 The Gold Mining Industry

Research on the gold mining industry focuses solely on the producers of this commodity, which sets them apart from their oil and gas counterparts. When looking into the risk management practices within the gold mining industry, Tufano (1996) explores gold price risk hedged by firms, both as a means to maximize firm value and as policies of risk-averse managers.

The evidence does not support theories that posit risk management can be used as a way to maximize shareholder value. Any theory that attempts to explain risk management as a mechanism to reduce the costs of financial distress, a firm's dependence on external financing, or as a means to reduce expected taxes is not strongly supported by the evidence presented by Tufano.

Continuing the investigation into the gold mining industry Tufano (1998) finds that gold mining firm exposures are inversely related to the amount of tis production that it hedges. Commodity risk management study that illustrates commodity price risk is reflected in stock market prices. Capital markets take firm-specific and market-specific factors into account when determining exposures of firms and, if given information on hedging activities, incorporate it into their valuation of the firms. Contradictory to Tufano, Adam and Fernando (2006) find that gold mining firms realize economically significant cash flow gains via their derivative transactions.

2.2.2 Oil and Gas Industry

Similar to Tufano (1996), Haushalter (2000) examines different motivations and to what extent firms hedge, focusing on oil and gas producers.

Haushalter finds evidence supporting the idea that financing costs can be alleviated by hedging, which supports Froot, Scharfstein, and Stein (1993). Mackay and Moeller (2007) model the value of corporate risk management in oil refinery companies, confirming that firms that hedge concave revenue can represent 2-3% of a firm's value.

Key to the value increase associated with hedging is that its firms who did not hedge input costs had more value than those who did hedge; partial hedging in increase value, fully hedging can cancel out any benefits. Yin and Jorion (2006) verify that an oil and gas producing firms' stock price sensitivity can be minimized with hedging. However, they do not find evidence that hedging increases a firm's Tobin's Q ratio, which they use a proxy for a firm's market value.

Contrary to Yin and Jorion, Carter, Rogers, and Simkins (2006a, 2006b) find a positive relationship between airline's use of jet fuel price risk derivatives and the firm's Tobin Q ratio. They posit that due to jet fuel comprising a large portion of airlines' operation costs, they have a strong incentive to hedge jet fuel price risk. High jet fuel prices coincide with low industry cashflow, and industry investment is positively related to the level of jet fuel costs. They increased value of firms that hedge is referred to as the hedging premium. Carter, Rogers, and Simkin's believe the hedging premium reflects that those firms with greater ability to take advantage of the benefits associated with hedging, such as enhanced ability to invest in economically profitable projects.

2.3 OTHER DERIVATIVE USAGE AND FIRM VALUE

Visvanathan (1998) examine firms' usage of interest rate swaps. This research does not look for a relationship between derivative usage and firm value, rather, it is a comprehensive study on firm characteristics of non-financial companies using interest rate swaps that comprise the S&P500 Index. Allayannis and Weston (2001) conduct research on the use of foreign currency derivatives (FDC) and their relationship to a firm's market value. Like Yin and Jorion (2006) and Carter, Rogers, and Simkins (2006b), they use Tobin's Q as a proxy measurement for a firm's market value.

Their evidence corroborates the positive relationship Carter et. al find regarding firm value and the use of derivatives, determining a hedging premium of 4.87% on average for firms that do hedge foreign currency risk. Bartram, Brown, and Conrad (2011) take an international approach, including firms from 47 countries when examining effects of derivative usage on a firm's value and risk. They find that derivative usage is associated with significantly higher firm value, abnormal returns, and larger profits in economic downturns.

Chapter 3: Methodology

3.1 DATA COLLECTION METHOD

3.1.1 Sample Selection

We studied large non-financial firms in the United States. Similar, to Visvanathan (1998), Nguyen (2011), and Angelis and Ravid (2017) we reviewed firms in the Standard and Poor's 500 Index. Excluding financial firms allowed us remove firms that write and use derivatives for trading and speculative purposes.

We acknowledged that does not fully eliminate the problem, however, and further refined our search by including only firms that do not use derivatives for speculative or trading purposes. Non-American companies were also excluded from our study, as we wanted to eliminate potential foreign country effects on our data.

Lastly, we narrowed our sample by focusing on a twelve-year span, from 2006 to 2017. While our data set has longer time frame than most of the similar research. It provides more information for our goal, which is to see how commodity prices impacted firm value and to additionally observe the effects of commodity price volatility in 2014 and the financial crisis in 2008-2009 impacted companies' derivative usage and firm values.

Hedging information for each company is obtained from their respective annual financial reports. These 10-K annual reports are filed with United States Security and Exchange Commission (SEC) and are found on their website and on each company's website.

Derivative and hedging information is found in item 7a Quantitative and Qualitative Disclosures about Market Risk as well as footnotes in the Financial Statements and Supplementary Data sections in each 10-K filing. Further information is obtained by employing a search within the text, using such terms as "derivative," "hedge," "commodity," "fuel," "energy," "swap," "future," and "forward contract." The result is sample of 316 firms and 3,792 firm years.

3.1.2 Dependent Variable

We use Tobin's Q ratio as a proxy for firm value measurement (Wernerfelt and Montgomery, 1988). In our study, Tobin's Q ratio is defined as the ratio between the market value of the firm over the replacement cost of its assets. Our methodology for constructing the market value and replacement cost of assets closely follows Lindenberg and Ross (1981).

The market value is a combination of common stocks, referred stocks, short-term debt-to-book value, and long-term debt. The replacement cost of a firm's assets is the sum of total assets, value added by market of total plant and equipment, and value added by market of inventories.

In our regression we use the natural logarithm transformation of Tobin's Q ratio. This is because the natural log of Tobin's Q ratios provides better statistical distribution properties (Hirsch and Seaks, 1993). As the Appendix A histogram shows, Tobin´s Q without logarithm form is obviously left skewed and more leptokurtic, while after doing the logarithm transformation, the distribution is more symmetric and less peaked.

3.1.3 Independent Variables

In order to authenticate the relationship between a firm's value and their use of derivatives, we need to eliminate the effect that all other variables could have an impact on a firm's value (Tobin's Q ratio). In this section we present the control variables used in our univariate and multivariate tests, as well as the reasoning behind their presence. We test our hypothesis in a univariate and multivariate setting.

We control for the following: *(1) firm size; (2) leverage; (3) profitability; (4) investment growth; (5) liquidity; (6) industry effect; and (7) time effect.*

(1) Firm Size: The predominant reasoning behind controlling for size is that large firms are more likely to use derivatives than smaller ones. Additionally, both size and leverage are proxies for a firm's financial distress. From Nguyen and Faff (2002) we know that financial distress costs increase disproportionately less as firm size increases. Therefore, we would expect that smaller firms would have more incentive to hedge, as it would reduce their probability of financial distress. We control for firm size by using the natural log of the firm's total assets as a proxy. We expect, like Nguyen and Faff (2002), that there is a positive relationship

between size and the decision to use derivatives, and a negative relationship between size and the extent of derivative usage.

(2) Leverage: Allayannis and Weston (2001) control for differences in firms' capital structure, as this is may be related to value. Taking the ratio of long-term debt over equity allows us to control for a firm's leverage. The higher a firm's leverage ratio, the higher the probability that a firm will face financial distress, ceteris paribus. Due to this, more highly levered firms will have more incentive to use derivatives in order to reduce their distress costs.

(3) Profitability: We control for profitability by using return on assets (ROA), calculated as a firm's net income divided by their total assets. We expect a positive association of profitability with ROA.

(4) Investment Growth: By using the ratio of capital expenditures to total sales, the ratio of R&D to total assets, and the ratio of advertising expenses to total assets as proxies, expecting a positive association of these proxies with Q.

(5) Liquidity: As a proxy for liquidity, we adopt the same calculation used by Carter, Rogers, and Simkins (2006b), taking the sum of a firm's cash and short-term investments, divided by sales. Excess cash can be a substitute for partaking in risk management and hedging.

(6) Industrial Effect: Firms have industry specific factors that make controlling for industry effects beneficial. Using industry controls at the 4-digit SIC and the industry-adjusted Qs in separate regressions.

(7) Time Effects: Using 11 different dummy variables for each year of our data set (2006-2017).

We exclude the following control variables that appear in previous research:

Industrial Diversification: Allayannis and Weston (2001) control for industrial diversification by using a dummy variable equal to 1 if a company operates in more than one segment, 0 if they do not. We assume a majority of S&P500 companies operate across multiple segments, and therefore this is not a beneficial control variable for our research.

Geographic Diversification: We already limit our research to American companies. While there are some firms listed on the S&P 500 index that do not have headquarters in the U.S., we eliminated these companies in our preliminary data collection process. Due to our chosen sample of companies, we do not believe any correction or control for geographic diversification is necessary.

Access to Financial Markets: The companies we have chosen to examine are some of the largest market cap companies in the U.S. Due to this fact, we assume each company has equal access to financial markets.

Credit Rating: Previous studies on derivative usage and firm value have controlled for companies' credit ratings. These studies have primarily focused on specific industries, such as oil and gas and airlines, or on the use of foreign currency and interest rate derivatives. Due to our diverse set of companies, and the fact that we are interested in their usage of commodity derivatives, we do not believe that credit rating plays an influential role in determining our companies' Tobin Q ratios. Previous research on interest-rate swap usage among non-financial companies in the S&P500 finds that credit quality is not significant in distinguishing between those firms that use swaps and those that do not Visvanathan (1998).

3.2 THEORETICAL FOUNDATION

During our research into firms' derivative usage, we found that there are several different methodologies and models in the literature that are used to see how commodity (and other) derivatives usage affect firm value. We discuss the two most common methods; simple linear regression model and generalized linear models (GLMs), as well as the drawbacks of each method.

3.2.1 Simple linear regression model

Simple linear regression is a straightforward and important example of a generalized linear model. In a linear regression, the use of the least-squares estimator is justified by the Gauss-Markov theorem, which requires assumptions of linearity, constant variance, and independence, but does not assume the distribution is normal. A simple linear regression model takes the expected value of the continuous variable, Y, as a linear function of the continuous predictor, X. One assumption is that Y is normally distributed, errors are normally distributed, independent, and that X is fixed and has a constant variance. From the perspective of generalized linear models, however, it is useful to assume that the distribution function is normal and has constant variance.

We examine two common uses of a linear regression in the literature:

a) Pooled Ordinary Least Squares (Pooled OLS)

A Pooled OLS estimation is an OLS technique used for panel data. For the normal distribution, the GLM has a closed form expression for the maximum-likelihood estimates, which is useful for our analysis. Most other GLMs lack closed form estimates. Therefore, all individually specific effects are completely ignored. Therefore, a lot of basic assumptions, such as the orthogonality of the error term, are violated.

As the pooled OSL is suited to analyzing panel data, which we have, we chose to adopt this method when analyzing our own data. The general formula for a panel data regression is:

$$y_{i,t} = \beta_0 + \beta_1 x_{i,t,1} + \beta_2 x_{i,t,2} + \cdots + \beta_k x_{i,t,k} + e_{i,t}$$

An important requirement when using a pooled OLS is that the panel data must be stationary and balanced, which ours is. The advantages of panel data is it allows us to focus on a broader range of issues and investigate more complex problems than if we created a simple time series or analyzed pure cross-sectional data alone.

Our inspiration to use pooled OLS model came from reading Allayannis and Westin (2001), who use this method to analyze the use of foreign currency derivatives (FDC) and firm value. Their research question is similar to ours, though focused on a different kind of derivative, FCD rather than commodity derivatives (CD).

These are two types of panel estimator approaches. The simplest type of fixed effects models allows the intercept (α) in the regression model to differ cross-sectionally but not over time, while the slope estimates (β_1)) are fixed both cross-sectionally and over time.

To see how the fixed effects model works, first we decompose the disturbance term, $e_{i,t}$, into an individual specific effect, $\mu_{i,t}$, and the "remainder disturbance," $\nu_{i,t}$, that varies over time and entities (capturing everything that is left unexplained about $y_{i,t}$).

$$u_{i,t} = \mu_{i,t} + \nu_{i,t}$$

We can rewrite the previous equation as:

$$y_{i,t} = \beta_0 + \beta_1 x_{i,t,} + \mu_{i,t} + \nu_{i,t}$$

The fixed effects method works best when there is a large T and small N. Also, if the error component, $v_{i,t}$ is correlated with the dependent variable X, using the random effect model would result in biased results, whereas the fixed effect model does not. This method is used by many in the literature when analyzing panel data regarding derivative usage by firms, including Tufano (1998), Allayannis and Weston (2001), Adam, T., Fernando, C. (2006), Nguyen, H., Faff, R. (2010), Bartram, S., Brown, G., Conrad, J. (2011), Coles, J., Lemmon, M., Meschke, J. (2012), Rampini, A., Viswanathan, A. (2014), Angelis, D., Ravid, S. (2016); Adam, T., Fernando, C., Salas, J. (2017). With this broad usage and given it works well with our dataset, we chose the fixed effects method.

Somewhat lesser used is the random effect model. This model also proposes different intercept terms for each entity (similar to FE), however, the difference is that under the random effects model, the intercepts for each cross-sectional unit are assumed to arise from a common intercept (α) which is the same for all cross-sectional units over time, plus a random variable, $\in_i$, that varies cross-sectionally but is constant over time. $\in_i$ measures the random deviation of each entity's intercept term from the 'global' intercept term, alpha. Can be written:

$$y_{i,t} = \alpha + \beta_1 x_{i,t} + \omega_{i,t}\ ,\ \omega_{i,t} = \in_i + v_{i,t}$$

Random effect model is preferable to the fixed effect model when N is large and T is small, the estimates of two models differ slightly, and when the cross-sectional groups are a random sample from the population. Carter, et. al. (2006a) and Carter, et. al. (2006b) use the random effect model in their paper on jet fuel hedging use by U.S. airlines.

b) Generalized method of moments (GMM)

As suggested by Magee (2013), if firm's value is correlated with its lagged values, we can use a dynamic model with system GMM estimators. When a lagged dependent variable as an independent variable (dynamic model structure) considers a possible autoregressive feature of the data. System GMM estimators were developed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). This model is suitable for small T and large N panels (Roodman, 2006). System GMM estimators of Blundell and Bond (1998) employ a first-difference transformation and use lagged values of endogenous variables in first differences equation.

GMM, as opposed to OLS, allows for simultaneity among the dependent variables by including the correlation of residuals across simultaneous regression equations. When researching how risk management can add value to a firm, Mackay and Moeller (2007) use non-linear GMM coefficient estimates in a pooled sample of 34 oil refiners. They regress the cost function and their associated derived output-supply and input-demand. GMM mitigates simultaneity bias that are caused by endogenous explanatory variables by using predicted (instrumented) values, rather than realized values of the endogenous variables. Used alongside Hansen’s J-statistic.

In our dynamic models with system GMM estimators, we accept first lag of dependent variable (natural logarithm of Tobin's Q ratio or industry adjusted Tobin's Q ratio), extent of hedging variable, natural logarithm of total assets, return on assets and financial leverage ratio as endogenous, while all other variables are accepted as exogenous.

3.2.2 Generalized Linear Models (GLMs)

The GLMs we will discuss here are the Logit and Probit Regression Models. These models are used when a traditional linear modelling framework has variables that are not normally distributed.

Also, traditional linear probability models can only produce probabilities that are between 0 and 1, whereas logit and probit models can produce estimated probabilities that are negative or greater than one. GLMs are most commonly used to model binary or count data and refer to a larger class of models popularized by McCullagh and Nelder (1982). Most of below discussion is based on John Fox’s (1997) treatment of Logit and Probit Regression Model.

a) The Logit Regression Model

It can be thought of as consisting of a mathematical transformation of a standard regression model.

$$\mathcal{F}(z_i) = \frac{e^{z_i}}{1 + e^{z_i}} = \frac{1}{1 + e^{-z_i}}$$

The primary reasons why the logit transformation function is used is that the residuals will not be normally distributed and they cannot be constant across values of X. Because Y has only two possible values 0 and 1, the residuals have only two possible values for each X. With only two possible values, the residuals cannot be normally distributed. Moreover, the best line to describe the relationship between X and Y is not likely to be linear, but rather an S-shape.

Instead of a normal distribution of errors, we assume the errors are logistically distributed. The basis of the logit link function is the cumulative frequency distribution, called a cumulative distribution function or CDF, that describes the distribution of the residuals. The binomial CDF is used because there are two possible outcomes.

b) The Probit Regression Model

It is a fairly simple transformation of the prediction curve and also provides odds ratios, and so it is popular among researchers.

$$\mathrm{F}(z_i) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z_i} e^{\frac{z_i^2}{2}} \, dz$$

If the true underlying variable we are predicting is continuous we can assume the errors are normally distributed. In this case, instead of using the binomial CDF, we can use a link function based on the normal CDF.

3.3 EMPIRICAL PROCEDURES

After we manually collecting the data about the usage of commodity derivatives, we formed a dummy variable that 0 represents no usage of commodity derivative mentioned in 10-K fillings and 1 represents using commodity derivatives. Meanwhile we also collected information from WRDS to calculate some firm characteristics, then we have a balanced panel data of 316 firms for 12 years.

There are several benefits for panel data. First, panel data can still work with omitted variable, when the time serious and cross-sectional data fails. While for our data set, there is no omitted variables. Moreover, the panel data provides more information cross time and cross sections. It is also less possibility of high level of multicollinearity and more degree of freedom (Baltagi, 2005), which is more a severe problem in time serious or cross-sectional data.

Our research question is: does using commodity derivatives for hedging purpose have significant effects on firm's value? For answering our research question that whether using derivatives add firm value or not or when they should use the derivative, by holding the firms characteristic constant or the time constant, there is no more efficient data combination to exam this.

There are several relevant methods in theoretical foundation part. While for one major method (GLMs) of dealing with binary data, Logit and Probit Regression Model is being used in previous research. Take Logit method as example, the big problem with binary data is that as fit a linear relationship between the binary variable as response variables and other explanatory variables.

While Logit model is suitable when the responds only take place in two possible values (Rodríguez, 2007). The binary variable makes almost impossible to get a stable and consistent regression as we mentioned before in theoretical foundation section. Not to mention this particular method is not suitable to answer our research question. It is perfect for another direction of the usage of commodity derivative research, that is to investigate what effect the firm's decision for using commodity derivatives.

Since the purpose of usage of commodity derivatives is hedging risk, in our empirical investigation we assume the impact of using commodity derivatives is contemptuously to the firm value. Companies are required to declare their use of derivatives since 2007, and the purpose of using derivatives is to hedge, not speculation for profit.

From a firm's perspective, the effective time of using commodity derivatives is known from the beginning of the contract because every derivative has expiry date even the underlying assets do not. Hence the effects of the using commodity derivatives are considered contemptuously. Without lag effect consider in our model setting, we ruled out using the system GMM estimator or dynamic panel with system GMM estimator. (Arellano and Bond, 1991, Arellano and Bover, 1995).

Meanwhile, because of the criterion of the data collection, we also assumed the firm we included, which are using commodity derivates, are highly likely expose to the specific commodity risk. It is consistent with the no speculation assumption. It also implies that the firm within the same industry may face the same risk, while the choice of using commodity or not may have effect on the firm's value.

After doing research, we think the Pooled OLS model is the most suitable with us to start with. The Pooled OLS estimator is consistent if the explanatory variables are not correlated with the error term. While there are techniques for dealing with the unobserved individual specific effects, such as the Fixed Effect estimation model and the Random Effects estimation model. We use software (MATLAB) to code step by step following the estimation method.

As we know, financial data is general not normally distributed, which were being discovered by Bird and McHugh (1977) along with other researchers. There is a drawback of using Pooled OLS model with financial ratio, Tobin's Q, hence, we first exam our explanatory variable (Tobin's Q) with comparing mean and median of the dataset. The mean of the Tobin's Q is 2.23 and the median is 1.80, which means the data is skewed. With more visualized way, we made the histogram of the distribution of the Tobin's Q (see appendix A), and it is obvious that there are few outliers. To remedy this, we use the natural logarithm transformation of the Tobin's Q to remedy the effect. The natural logarithm transformation of the Tobin's Q has mean of 0.65 and median is 0.59. With another histogram, the skewness level is obviously reduced.

We did several univariate tests. First, we did under the null hypothesis that the usage of the commodity derivatives does not impact the firm's value, so as to the other firm characteristic. Take Firm's value, proxied by Tobin's Q, it means that the average or the median of Tobin's Q of the firm that use commodity derivatives is not statistically different to the average of Tobin's Q of the firm that does not use commodity derivatives.

As the mean value of Tobin's Q is higher than the median value of Tobin's Q, even with logarithm, suggesting that the distribution of Tobin's Q is still slightly skewed, we test our hypothesis using both means and medians. Second, with the null hypothesis that the mean of users and non-users within the same industry are not statistically significant different, while firms face similar risks when it comes to hedging with certain commodity derivatives.

In addition, we used Student t-test is a statistical test which is widely used to compare the mean of two groups of samples, commodity user and commodity non-user. It is therefore to evaluate whether the means of the two sets of data are statistically significantly different from each other. We also did p-value for t-statistic of the hypothesis test that the corresponding coefficient is equal to zero or not. For testing the null hypothesis of that the two medians of two sample are statistically same, we use the Wilcoxon signed rank sum test, a non-parametric test, which allow us to using z-statistics to test our null hypothesis.

Then we did the multivariate test with panel data with response variable (the Tobin's Q in logarithm) with the explanatory variables (the dummy variables of commodity usage). Because Tobin's Q may be affected by other factors, such as size, leverage, profitability, investment growth and liquidity. We use control variables mentioned above to single out the effect of using commodity derivatives on firm's value. While for industrial effect, we run the separate regression for different industries with all other same variables.

$$Ln(Tobin's\ Q) = \alpha + \beta \times Commodity\ dummy + \sum\nolimits_j \gamma_j \times Control\ variable_j + \varepsilon$$

$$\begin{aligned} Ln(Tobin's\ Q) = \alpha + \beta \times Commodity\ dummy + \gamma_1 \times Firm\ Size + \gamma_2 \times Leverage \\ + \gamma_3 \times Profitability + \gamma_4 \times Investment\ Growth + \gamma_5 \times Liquidity + \varepsilon \end{aligned}$$

We run a Pooled OLS with our panel data, and then for checking the model with the unobserved effect, we use the Fixed Effect estimation model with taking first difference and the Random Effect estimation model.

For the Fixed Effect estimation model, we use Chow Test under the null hypothesis that the usage of the commodity derivatives does not impact the firm's value, so as to the other firm characteristic, with the F-statistics for one way Chow test to see if there Fixed Effect.

We did the F-statistic to check that we did correct way to do Pooled OLS, under the null hypothesis is that all coefficients are equal, therefore fixed effect exists. While the Random Effects are firm specific, in our regression, we use the control variable for firm characteristics that may have some affect the firm's value, so we do not have to do the random effect regression.

In the end, we did sensitive test on our model. First, we have w new firm characteristic ratio as alternative control variable besides the alternative method of Tobin's Q calculation. Instead of doing a regression with the alternative control variables, we did descriptive statistic with the original Tobin's Q, we compare the correlations, mean, median and the standard deviation. Then we adapted run a Pooled OLS with the alternative method of the Tobin's Q as the Y and the original control variables, to check the result of the regression are not unique with the proxy we used. We observed the difference of the corresponding coefficients and the statistics between the original Tobin's Q and the alternative Tobin's Q.

3.4 IMPROVEMENT

We collected data based on the list of firms in the S&P 500 Index. It limited the data to certain size of United States firms. Almost all firms in S&P 500 used derivatives, mostly foreign exchange currency and interest rate. Therefore, it is difficult to find firms who do not use derivatives. We could improve that by collecting data through survey. We have seen this method used in other papers we have read during our research.

With more time and more specific data, we could try other estimation methods for estimating coefficients, by comparing different estimators, we could infer how accurate the fixed effect estimations are. Therefore, we would have been able to infer more convincing datapoints and conclusions.

Chapter 4: Analysis and Discussion

4.1 DATA ANALYSIS

Since we are interested in the effect the usage of commodity derivatives has on firm value and the potential impact on firm value of change in hedging policy, we examine first the use of commodity derivatives over time for the firms in our sample.

Table 1
Number of firms using different commodities

		Hard Commodities										Soft Commodities	
	All Commodity		Energy									Livestock and	
	Usages	Metals	Chemicals	Crude Oil	Natural Gas	Heating Oil	Coal	Uranium	Fuel Oil	Electricity		Meat	Argicultural
2006	115	30	3	23	59	1	11	2	34	29		6	18
2007	116	31	3	23	60	1	11	2	34	28		6	18
2008	118	32	3	23	61	1	11	2	35	28		6	19
2009	119	32	3	23	61	1	11	2	36	28		6	19
2010	118	32	3	23	61	1	12	2	34	29		6	19
2011	119	33	3	23	61	1	13	3	35	29		6	19
2012	119	33	3	23	62	1	12	3	35	29		6	20
2013	120	34	3	24	62	1	11	5	36	28		6	20
2014	118	32	3	24	62	1	11	5	36	28		6	20
2015	117	31	3	24	62	1	11	5	36	28		6	20
2016	118	31	3	24	62	1	11	5	37	28		6	20
2017	117	30	3	24	62	1	11	5	36	28		6	20
Average	117.83	31.75	3.00	23.42	61.25	1.00	11.33	3.42	35.33	28.33		6.00	19.33
Percentage	37.29%	26.94%	2.55%	19.87%	51.98%	0.85%	9.62%	2.90%	29.99%	24.05%		5.09%	16.41%

Table 1 describes the amount of the usage of the commodities over years for different type of representative commodities. It provides frequency of different commodity derivatives usage among United States non-financial firms over years. Of the 316 total firm observations, we identify 117 (37.29%) average firms using commodity derivative from 2006 to 2017. When we observe more detail about different types of commodity hedges, we identify Natural Gas (51.98%) is the most popular commodity hedge through industry, followed by Fuel Oil (29.99%), and Metals (26.94%) for the second and third common commodity usage respectively. Not as we expected that during for the spike of the financial crisis time from 2007 to 2009 or the 2014 oil crisis.

Table 2
Summary statistics

	Mean	Median	Std. Dev.	10th Percentile	90th Percentile
Tobin's Q	0.653	0.587	0.517	0.031	1.375
Firm Size	9.366	9.376	1.301	7.752	10.916
Leverage	0.471	0.456	7.995	0.000	1.554
Profitability	0.066	0.067	0.088	0.009	0.148
Investment Growth	0.179	0.082	1.375	0.019	0.311
Liquidity	0.073	0.034	0.594	0.010	0.116

There are 3792 firm-year observations, 316 firms per year for 12 years, we demonstrate that the mean of the Tobin's Q (in the natural log form) is slightly higher than the median of the Tobin's Q, implies the distribution is slightly skewed. When collated using our method of logarithm transformation, it is more symmetric and less problematic for later regressions. Meanwhile, the investment growth and the liquidity ratio are most skewed among all variables. It is also surprising that the mean and median of the firm size or the profitability are not obviously different.

Table 3
Descriptive statistics

	User		Non-User		Difference tests		
	Mean	Median	Mean	Median	Expected Sign	Mean	Median
Tobin's Q	0.421	0.316	0.793	0.722	+	-0.372*	-0.406*
Firm Size	9.899	9.953	9.045	8.935	+	0.854*	1.018*
Leverage	0.475	0.579	0.468	0.394	+	0.007	0.185*
Profitability	0.054	0.050	0.074	0.075	-	-0.019*	-0.025*
Investment Growth	0.173	0.100	0.183	0.073	-	-0.010	0.027*
Liquidity	0.038	0.030	0.094	0.038	-	-0.056*	-0.008*

Notes: The different tests are a paired sample t-test for mean difference and z-test for median difference.
* Significant at the 95% confidence interval

In the table above, we calculated the mean and the median of the variables. For the Tobin's Q and the firm size, as the proxies of the firm values, the mean and the median of the user Tobin's Q are statistically significant different to the mean of the non-users. We expected that the users have average higher firm value because of the hedging behaviours indicate more stable revenue being rewarded by investors as Lau (2016) found for empirical analysis for corporate derivative hedging. While for firm size, our finding agrees with Lau (2016) and as we expected (+) that the users have bigger firm size, indicating they have better access to financial market. It is worth to point out that the firm lack of liquidity or profitability will more likely to engage commodity hedging activities as we expected (-).

There is no statistical significance for the mean of the users leverage or investment growth compared to the mean of the non-users leverage, while for median, the users leverage median is statistically significantly larger than the non-users leverage median. This implies that user's distribution of the leverage or investment growth is more right skewed than non-users. For leverage, we expected a positive relationship with the usage of the commodity derivatives, while the median result supports our expectation.

On the contrary, the investment growth an opposite relationship to what we expected, the higher median for users, we think it can be explained as that the firms with higher investment growth (median) are more willing to engage commodity hedging more stable future revenue, in another word, more enthusiastic to ensure the future.

Table 4
Correlation coefficients among independent variables

	Tobin's Q	Firm Size	Leverage	Profitability	Investment Growth	Liquidity
Tobin's Q	1.000					
Firm Size	-0.482	1.000				
Leverage	-0.038	0.019	1.000			
Profitability	0.360	-0.075	-0.020	1.000		
Investment Grow	0.041	-0.080	-0.002	-0.211	1.000	
Liquidity	0.079	-0.103	-0.005	-0.179	0.965	1.000

We report correlation coefficients between independent variables in Table 4. Correlation coefficients are relatively low, which implies that possibility of facing multicollinearity problem is low. If the firm has more cash or short-term investments at hand, higher liquidity, there are positively correlated to the firm's investment growth (0.965). As we expected, the higher liquidity of the firm, the better access to financial market and the better grow opportunities.

4.2 EMPIRICAL RESULTS

4.2.1 Univariate Tests

Under the null hypothesis that the usage of the commodity derivatives does not impact the firm's value, so as to the other firm characteristics.

Table 5
Univariate tests: difference tests for mean and median

		Mean			Median		
	Expected Sign	Difference	t-stats	p-value	Difference	z-stats	p-value
Tobin's Q	+	-0.372*	-22.848	0.000	-0.406*	-23.036	0.000
Firm Size	+	0.854*	20.662	0.000	1.018*	20.440	0.000
Leverage	+	0.007	0.024	0.981	0.185*	13.039	0.000
Profitability	-	-0.019*	-6.586	0.000	-0.025*	-12.556	0.000
Investment Growth	-	-0.010	-0.217	0.828	0.027*	10.088	0.000
Liquidity	-	-0.056*	-2.811	0.005	-0.008*	-8.557	0.000

Notes: The different tests are a paired sample t-test for mean difference and z-test for median difference.
* Significant at the 95% confidence interval

According to the main hypothesis of the study, firms using commodity derivatives for hedging are valued higher than non-users. In order to empirically investigate this hypothesis, a test of equality of mean values of firm value and control variables is conducted to make a comparison among hedgers and non-hedgers.

The resulting univariate tests show that the mean and the median are statistically significantly different when it comes to Tobin's Q, firm size, profitability and liquidity. It implies that the using of commodities has empirical relationship with the firm characteristics. Even for the two variables that the mean is not statistically different between the users and not users, the median is statistically significant. In this case, we will use them all as control variables for the regression.

For univariate test, we are interested in the time variate on the hedging behaviour with the firm's value and other firm characteristics. There is no obvious pattern for different firm characteristics through time, we additionally did not find obvious patterns for the financial crisis or the oil crises. (See appendix B for more details)

4.2.2 Multivariate Tests

While the univariate tests described in the previous section indicates that derivatives users generally performed better than the non-users on all the measures, there is a need to control for variables that could have an impact on these performance measures. This study therefore uses multivariate tests to further verify the preliminary findings based on the univariate tests.

Impact of derivatives usage on firm value is estimated through the model Allayannis and Weston (2001) which has been commonly used in prior studies:

$$Ln(Tobin's\ Q) = \alpha + \beta \times Commodity\ dummy + \sum_j \gamma_j \times Control\ variable_j + \varepsilon$$

In the above given equation, Tobin's Q is taken as a measure of firm value while natural log is taken to control the skewness of the variable. α is the constant coefficient, β is the coefficient of use of commodity derivative, γ is the coefficient of control variables and ε is the error term.

One advantage of balanced panel data is that it allows controlling the potential existence of non-observable individual characteristics that may vary across cross-sections but remain constant over time. Panel data is comprised of different cross-sections over time so the element of heterogeneity is must (Baltagi, 1995) and simple Pooled OLS regression does not account for the individual heterogeneity and leads to biased estimations. Due to this limitation of OLS technique, most of the researchers have used different techniques from OLS like Random Effect or Fixed Effect model.

Table 6
Multivariate test: Cross-section results

	Pooled Regression	Fixed Effect	Random Effect
R-Square	0.378	0.128	0.444
Intercept	2.036*	0.000*	2.431*
Commodity Dummy	-0.196*	-0.260*	-0.181*
Firm Size	-0.154*	-0.135*	-0.172*
Leverage	-0.002	0.000*	-0.002*
Profitability	1.949*	0.397*	1.897*
Investment Growth	-0.013	0.002*	-0.021*
Liquidity	0.107*	-0.012*	0.128*
D1			-0.274*
D2			-0.249*
D3			-0.476*
D4			-0.374*
D5			-0.319*
D6			-0.346*
D7			-0.284*
D8			-0.165*
D9			-0.100*
D10			-0.102*
D11			-0.073*

Notes: T-statistics are based on White (1980) standard errors
* Significant at the 95% confidence interval

This table represents the results for Pooled OLS, Fixed Effect and Random Effect regressions of the use of commodity derivative on firm value. Under the null hypothesis of this the Chow test for Fixed Effect, the F-statistic is 0.172, and critical value is 1.972 at 95% confidence level, hence we cannot reject the null hypothesis.

We need to run a Fixed Effect regression for dealing with this effect. While as we assume the control variable with remedy the firm effects, we still run the Random Effect to observe the coefficients. Test statistics are presented in the form of tables of regression analysis. The null hypothesis of no correlation between individual effects and independent variables is rejected at 1% significance level. Test results illustrate that fixed effect model is more suitable for estimating Tobin's Q equation.

We explore a final econometric analysis using a Fixed Effect model that attempts to shed additional light on the relationship between firm risk and the use of derivatives. The use of a Fixed Effect model is inspired by the interesting results found in the univariate analysis based on portfolios discussed earlier.

Three main conclusions can be drawn from the results of the Fixed Effect model and the Random Effect model.

First, there is some evidence indicating that the limited success of the Pooled OLS model in documenting a significant relationship between firm risk and derivative use, using a continuous proxy, may be attributable to the nonlinearity of the relationship. Second, after controlling the Fixed Effect, the coefficients are all statistically significant and more severe discount on firm's value for commodity derivative users. Third, for the random effect model, with controlling the time with the dummy variables, the R-Square increased significantly, as well as the coefficients of the profitability and the investment growth.

To some degree, it is not surprising that the profitability has significant positive relationship with the Tobin's Q, but the negative relation with the investment growth is interesting and puzzling. It is opposite as we expected of the relationship between investment growth and Tobin's Q with commodity usage considered. The table also indicates regression results for all hedgers including currency risk, interest rate risk and commodity price risk hedgers. Following studies in the literature, we estimate Fixed Effect panel data model with time dummies for Ln Tobin's Q as dependent variables and derivatives use as independent variables.

Our results imply that non-financial companies can increase their value by hedging with financial derivatives. However, this hedging premium is very low compared to findings of Allayannis and Weston (2001) for the US data (5%) and Panaretou (2013) for the UK data (6%).

Our results also indicate that some control variables can explain firm value. Firm size is negatively related to firm value and coefficients are statistically significant in all models. Dividend dummy variable has a statistically significant positive coefficient and it implies that easy access to financial markets increases firm value. Coefficients of all other control variables are statistically insignificant.

4.2.3 Industry Effect

Table 7
Univariate tests: Industry Effect

		Economic Sector									
		Transportation	Utilities	Health Care	Capital Goods	Energy	Technology	Basic Materials	Communication Services	Consumer Cyclicals	Consumer Staples
Amount	Total	14	29	37	36	21	61	17	2	56	43
	User	9	29	1	13	21	4	10	0	12	25
	Non-User	6	0	36	26	0	59	7	2	46	21
Tobin's Q	User	0.336	0.052	0.570	0.549	0.319	0.614	0.393	0.000	0.472	0.892
	Non-User	0.726	0.000	0.932	0.664	0.000	0.853	0.692	0.235	0.754	0.725
	t-stat	-5.486	0.000	-1.948	-3.157	0.000	-3.499	-7.871	0.000	-6.166	3.704
	p-value	0.000	0.000	0.052	0.002	0.000	0.000	0.000	0.000	0.000	0.000
Firm Size	User	9.886	10.327	9.283	10.135	10.150	10.526	9.550	0.000	9.535	9.271
	Non-User	9.356	0.000	8.876	9.126	0.000	8.925	8.753	12.477	8.939	9.502
	t-stat	3.421	0.000	0.846	8.270	0.000	8.694	7.064	0.000	5.702	-2.199
	p-value	0.001	0.000	0.398	0.000	0.000	0.000	0.000	0.000	0.000	0.028
Leverage	User	-0.001	0.868	0.334	0.916	0.353	0.266	0.795	0.000	-0.009	0.166
	Non-User	0.292	0.000	0.352	1.438	0.000	0.502	0.693	0.814	0.354	-0.404
	t-stat	-0.174	0.000	-0.020	-0.503	0.000	-0.579	0.808	0.000	-0.350	0.491
	p-value	0.862	0.000	0.984	0.615	0.000	0.563	0.420	0.000	0.727	0.624
Profitability	User	0.044	0.024	0.080	0.067	0.033	0.115	0.056	0.000	0.052	0.098
	Non-User	0.084	0.000	0.048	0.080	0.000	0.075	0.074	0.040	0.086	0.078
	t-stat	-2.495	0.000	0.817	-2.355	0.000	2.709	-1.919	0.000	-5.513	3.297
	p-value	0.014	0.000	0.414	0.019	0.000	0.007	0.056	0.000	0.000	0.001
Investment Growth	User	0.119	0.231	0.122	0.072	0.386	0.208	0.104	0.000	0.075	0.050
	Non-User	0.082	0.000	0.553	0.065	0.000	0.170	0.093	0.156	0.052	0.050
	t-stat	2.803	0.000	-0.369	1.985	0.000	2.123	0.976	0.000	3.698	-0.247
	p-value	0.006	0.000	0.712	0.048	0.000	0.034	0.330	0.000	0.000	0.805
Liquidity	User	0.026	0.037	0.043	0.026	0.047	0.109	0.031	0.000	0.022	0.040
	Non-User	0.030	0.000	0.270	0.033	0.000	0.090	0.027	0.039	0.039	0.034
	t-stat	-1.173	0.000	-0.450	-2.711	0.000	2.052	1.641	0.000	-4.644	2.357
	p-value	0.243	0.000	0.653	0.007	0.000	0.041	0.102	0.000	0.000	0.019

Under the null hypothesis that the mean of users and non-users within the same industry are not statistically significant different, while firms face similar risks when it comes to hedging with certain commodity derivatives.

When we conducted the univariate tests cross the industries, there are some unexpected results. First, the industries that all the firm, that meet our data collection requirements, are almost 100% hedged with commodities derivatives. We expected the energy section will have high percentage of the firm hedge with commodities, since the energy price such as oil or natural gas is known for being volatile. While the utility and healthcare are not expected to have a high percentage of hedging. We excluded the communication section because the sample size is too few.

We also suspect that the utility and the healthcare may face some industrial specific risk which leads these two industries are enthusiastic to using commodity derivatives.

4.2.4 Time Effect

As Allayannis and Weston (2001) shown empirically, the behaviour of the dollar during the year is also likely to influence the value of firms with exposure. If firms with foreign sales are generally long foreign currencies, their value will go up when the dollar depreciates and fall when the dollar appreciates. Then, for the hedgers and non-hedgers, the firm value of non-hedgers may be benefit from the dollar depreciation while they will be hurt financially when dollar appreciation.

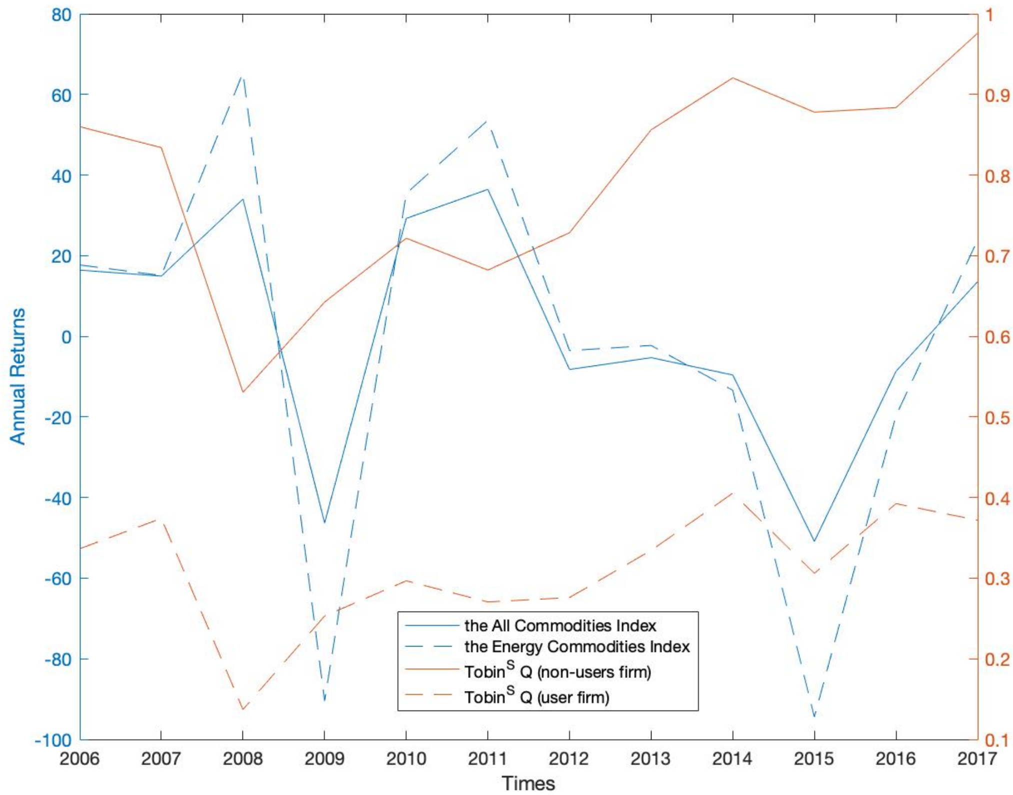
We also test our hypothesis that for two different directions of the price of commodity index, there is statistically same as what Allayannis and Weston (2001) found out empirically.

Table 8
Effect of prices fluctuation

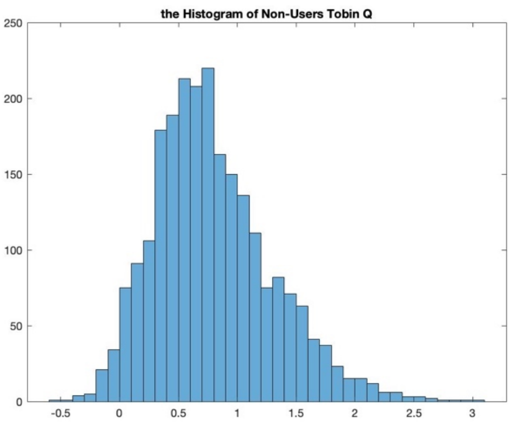
	Price goes up					
	Tobin's Q	Firm Size	Leverage	Profitability	Investment Growth	Liquidity
User	0.405	9.799	0.528	0.063	0.162	0.037
Non-User	0.768	8.906	0.333	0.070	0.232	0.118
p-value	0.000	0.000	0.608	0.096	0.435	0.030
	Price goes down					
	Tobin's Q	Firm Size	Leverage	Profitability	Investment Growth	Liquidity
User	0.438	9.999	0.421	0.045	0.184	0.039
Non-User	0.818	9.184	0.604	0.077	0.132	0.070
p-value	0.000	0.000	0.628	0.000	0.002	0.032

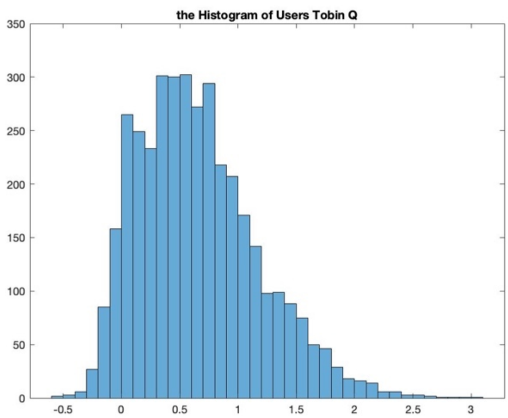
We are surprised by the univariate test results because the users and non-users Tobin´s Q, firm size and the liquidity are statistically significant to each other in both scenarios. Meanwhile, it is also obvious that the firm value of the non-users are always higher than the users.

Then we decide to do another analysis. First we plot the following figure:



As it can be observed, the firm value of users are not significantly worse or better in crisis time.





However, we plot the histogram for both, as it shown, the distribution of the non-users' firm value displayed more peak than the user´s. It is reasonable for users have lower firm value because for hedging purpose, there is not an intention to make profit, the firm´s value and the distribution indicate the commodity derivatives serve as insurance for the users. It provides more stable revenue with price.

4.2.5 Sensitivity Analysis

Here we adapt an alternative way for calculate Tobin´s Q, with two new selected control variables, the Book-to-Market ratio and the Market-to-Sale ratio.

Table 9
Alternative measures of Tobin's Q

	Correlation	Mean	Median	Std. Dev.	10th Percentile	90th Percentile
Tobin's Q	1.000	0.658	0.592	0.516	0.044	1.379
Alternative Tobin's Q	0.969	0.413	0.358	0.605	-0.300	1.236
Book-to-Market	-0.641	0.256	0.229	0.168	0.076	0.488
Market-to-Sale	0.272	3.508	2.778	5.778	1.056	6.059

In the table below, the alternative Tobin's Q is highly correlated with the original one, and the alternative control variables are also correlated to the original Tobin's Q.

Then we replace the original Tobin's Q by the alternative Tobin's Q in the Pooled OLS regression with the same control variables:

Table 10
Sensitivity Analysis

	Original Pooled Regression			Alternative Pooled Regression		
n = 3972	Coefficient	t-stats	p-value	Coefficient	t-stats	p-value
Intercept	2.043	40.598	0.000	1.971	32.234	0.000
Commodity Dummy	-0.194	-13.199	0.000	-0.171	-9.787	0.000
Firm Size	-0.154	-28.566	0.000	-0.176	-26.965	0.000
Leverage	-0.001	-1.785	0.074	-0.002	-1.625	0.104
Profitability	1.888	24.321	0.000	2.317	24.651	0.000
Investment Growth	-0.037	-1.957	0.050	0.001	0.060	0.952
Liquidity	0.036	3.617	0.000	0.084	2.505	0.012
R-Square	0.377			0.341		

The estimated coefficients for the alternative Tobin's Q is roughly similar level to the original one, with all the other condition remain the same, we think the proxy of firm value in our original research is a relatively valid choice.

Chapter 5: Conclusions

This paper examines the use of commodity derivative in the sample of 316 non-financial firm between 2006 and 2017. We examine whether firms with commodity exposure that using commodity derivatives are being rewarded by the investors with higher market valuation.

We use Tobin´s Q as the firm´s value proxy with the panel data. By using the Pooled OLS and the Fixed Effect, we find out the negative relationship with the commodity use with the firm´s value both in univariate tests and multivariate tests.

We also find that with commodity derivatives, the distribution of the Tobin´s Q of the hedgers are less peaked than that of the non-users. It can be explained by risk and return. When the firm uses the commodity derivative to hedge the risk, there is less risk of the firm in daily operation, hence the return implied is lower. It also collaborates that our assumption of data collection to some degree is reasonable, firm with commodity derivative is for hedge, not for speculation.

We were unable to find an empirical relationship of the commodity derivatives with the financial crisis or the oil crisis. This result is surprising to us, and we believe could serve as an area of further study and research.

Bibliography

Allayannis, George, and Weston, James P. (2001) The use of foreign currency derivatives and firm market value. *The Review of Financial Studies*, *14*(1), 243-276.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: monte carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29-51.

Bartram, S. M. (2017). Corporate hedging and speculation with derivatives. *Journal of Corporate Finance, 57*(8), 9-34.

Baltagi, B. H. (1995) Editor's introduction panel data. *Journal of Econometrics, 68*(1), 1-4.

Baltagi, B. H. (2005). Econometric analysis of panel data 3rd Edition England JW &Sons.

Ben Khediri, K. (2010). Do investors really value derivatives use? Empirical evidence from France. *The Journal of Risk Finance*, *11*(1), 62-74.

Bird, R. G., & McHugh, A. J. (1977). Financial ratios—an empirical study. *Journal of Business Finance & Accounting, 4*(1), 29-46.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115-143.

Carter, D., Rogers, D., & Simkins, B. (2006a). Does hedging affect firm value? evidence from the U.S. airline industry. *Financial Management*, *35*(1), 53-86.

Carter, D., Rogers, D., & Simkins, B. (2006b). Hedging and value in the U.S. airline industry. *Corporate Risk Management*, *18*(4), 21-33.

Fox, J. (1997). *Applied regression analysis, linear models, and related methods*. Sage Publications, Inc.

Froot, K., Scharfstein, D., Stein, J. (1993). Risk management: coordinating corporate investment and financing policies. *The Journal of Finance, 48*(5), 1629-1658.

Haushalter, David. (2000). Financing policy, basis risk, and corporate hedging: evidence from oil and gas producers. *The Journal of Finance, 55*(1), 107-152.

Hausman, J. A., and Taylor, W. E. (1981). Panel Data and Unobservable Individual Effects. *Econometrica: Journal of the Econometric Society*, 1377-1398.

Hirsch, B. and Seaks, T. (1993). Functional form in regression models of tobin's q, *The Review of Economics and Statistics, 75*(2), 381-385.

Lindenberg, E.B. and S.A. Ross. (1981) Tobin's q ratio and industrial organization. *Journal of Business,* (January), 1-32.

Long, J. Scott. (1997). Regression Models for Categorical and Limited Dependent Variables, *Advanced Quantitative Techniques in the Social Sciences*, *7*.

Magee, S. (2013). Foreign Currency Hedging and Firm Value: A Dynamic Panel Approach. In *Advances in Financial Risk Management* (pp. 57-80). Palgrave Macmillan, London.

McCullagh and Nelder (1982).

Modigliani, F., and Miller, M., (1958). The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review, 48*(3), 261-297.

Nance, D., Smith, C., and Charles W. Smithson. (1993). On the Determinants of Corporate Hedging. *The Journal of Finance, 48*(1), 267-284

Nguyen, H., & Faff, R. (2002). On the determinants of derivative usage by Australian companies. *Australian Journal of Management, 27*(1), 1-24.

Nguyen, H., & Faff, R. (2010). Are firms hedging or speculating? The relationship between financial derivatives and firm risk. *Applied Financial Economics*, *20*(10), 827-843.

Rodríguez, G. (2007). Lecture Notes on Generalized Linear Models. URL: http://data.princeton.edu/wws509/notes/

Smith, C., Stulz, R. (1985). The Determinants of Firms' Hedging Policies. *The Journal of Financial and Quantitative Analysis, 20*(4), 391-405

Stulz, Rene M. (1984). Optimal Hedging Policies. *The Journal of Financial and Quantitative Analysis, 19*(2), 127-140.

Tufano, Peter. (1996). Who Manages Risk? An Empirical Examination of Risk Management Practices in the Gold Mining Industry. *The Journal of Finance, 51*(4), 1097-1137.

Tufano, Peter. (1998). The determinants of stock price exposure: Financial engineering and the gold mining industry. *The Journal of Finance, 53*(3), 1015-1052.

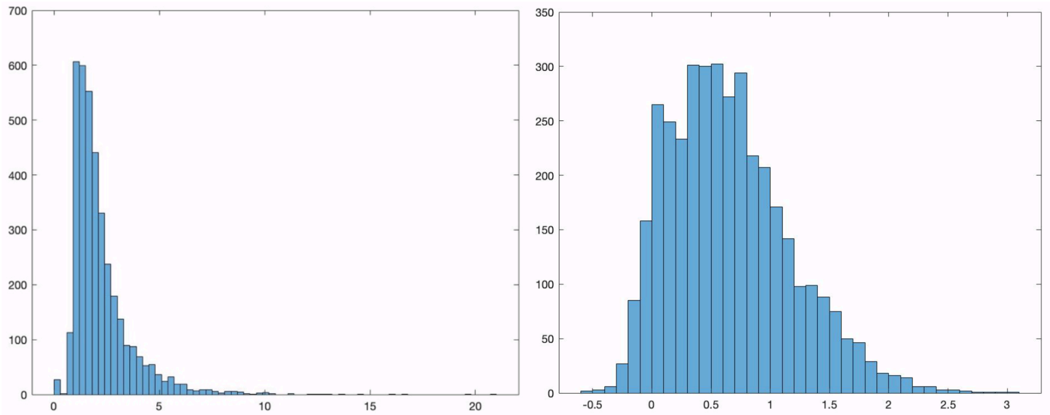
Visvanathan, Gnanakumar. (1998). Who Uses Interest Rate Swaps? A Cross-Sectional Analysis. *Journal of Accounting, Auditing, and Finance, 13*(3) 173-200.

Wernerfelt, B., and Montgomery, C. (1988). Tobin's q and the importance of focus in firm performance. *The American Economic Review, 78*(1), 246-250.

Woolson, R. F. (2007). Wilcoxon signed-rank test. Wiley encyclopedia of clinical trials, 1-3.

Appendices

Appendix A



The histogram of the distribution of the Tobin's Q, the left histogram without using natural logarithm, the right histogram with using natural logarithm. As the histogram shows, the distribution from the left to the right are less skewed and lower level of kurtosis.

Appendix B

Table
Univariate tests over time

		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Tobin's Q	User	0.441	0.471	0.244	0.335	0.384	0.350	0.366	0.461	0.495	0.452	0.525	0.549
	Non-User	0.864	0.837	0.532	0.644	0.724	0.682	0.729	0.857	0.922	0.880	0.885	0.978
	t-stats	-7.982	-6.459	-5.782	-6.394	-6.393	-6.160	-6.773	-7.105	-7.551	-7.266	-6.416	-7.114
	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firm Size	User	9.563	9.643	9.687	9.723	9.833	9.906	9.996	10.037	10.077	10.065	10.099	10.157
	Non-User	8.575	8.705	8.746	8.811	8.908	9.005	9.094	9.179	9.266	9.337	9.416	9.501
	t-stats	6.298	6.145	6.389	6.300	6.519	6.431	6.525	6.349	6.077	5.498	5.200	5.064
	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Leverage	User	-1.498	0.809	0.167	0.518	2.051	1.240	-1.123	0.737	0.979	0.160	1.263	0.364
	Non-User	-0.752	0.453	0.523	0.463	0.590	0.687	1.221	0.748	0.701	0.379	0.119	0.505
	t-stats	-0.407	2.741	-0.719	0.273	1.581	1.682	-1.559	-0.013	1.353	-0.177	1.538	-0.177
	p-value	0.684	0.006	0.473	0.785	0.115	0.093	0.120	0.990	0.177	0.859	0.125	0.859
Profitability	User	0.078	0.073	0.047	0.044	0.062	0.067	0.057	0.060	0.060	0.018	0.034	0.051
	Non-User	0.070	0.070	0.045	0.059	0.079	0.080	0.077	0.082	0.083	0.079	0.080	0.076
	t-stats	0.717	0.199	0.134	-1.433	-2.356	-1.683	-2.426	-3.090	-3.234	-4.607	-5.381	-3.260
	p-value	0.474	0.842	0.893	0.153	0.019	0.093	0.016	0.002	0.001	0.000	0.000	0.001
Investment Growth	User	0.146	0.163	0.159	0.153	0.158	0.169	0.189	0.180	0.193	0.208	0.179	0.175
	Non-User	0.529	0.161	0.335	0.202	0.127	0.125	0.117	0.117	0.119	0.120	0.120	0.116
	t-stats	-0.790	0.059	-0.717	-0.540	1.028	1.788	3.323	3.277	3.594	4.466	3.399	3.559
	p-value	0.430	0.953	0.474	0.590	0.305	0.075	0.001	0.001	0.000	0.000	0.001	0.000
Liquidity	User	0.084	0.087	0.085	0.126	0.131	0.119	0.116	0.125	0.116	0.126	0.149	0.134
	Non-User	1.057	0.318	0.520	0.642	0.337	0.307	0.292	0.300	0.308	0.291	0.300	0.301
	t-stats	-1.064	-3.338	-1.311	-1.457	-3.549	-4.662	-4.802	-5.271	-5.457	-4.765	-4.084	-4.647
	p-value	0.288	0.001	0.191	0.146	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000