The Impact of Fundamental Accounting Signals on Option Returns

By

Yuan Sun

A00362686

A research project submitted in partial fulfillment of the requirement for the degree of Master of Finance

Saint Mary's University

Written for MFIN 6692 under the direction of Dr. Francis Boabang

Approved by: _____Dr. Francis Boabang_____

Faculty Advisor

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MFin. Director

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Abstract

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The purpose of my research work is to investigate whether fundamental accounting signals have a significant influence on the option returns. The fundamental accounting signals released by companies will have a deep effect on the extreme stock price movement, and the option return is associated with the price of its underlying equity security. Results of the research work reveal that investors can use fundamental accounting signals to predict and gain significant option returns. According to the result, I can conclude that the fundamental accounting signals have significant and positive relationship with the option returns.

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Chapter 1 Introduction

1.1 Fundamental Accounting Signals

In this paper, I will use fundamental accounting signals to examine whether there is a positive correlation between fundamental accounting signals and the option returns. Specifically, I think both sales amounts and net incomes will be the most significant accounting target in valuing the company's performance and I will represent sales and incomes as volatility both in long-term and short-term. More importantly, this signal will give the investors predictive information about the company's stock price movements. Thus, fundamental accounting signals will be a crucial factor that influence option returns. Because option returns will be definitely correlated with the price movements of its underlying equity security.

1.2 Option Return and Straddle Contract

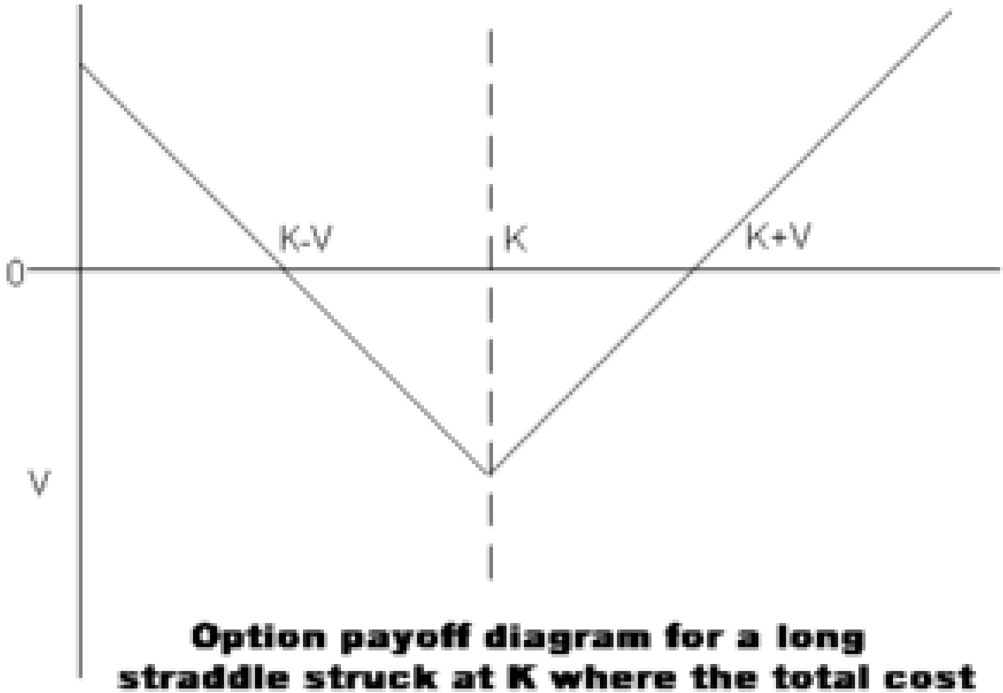
Based on the purpose of this research paper, I would like to offer the definition of option first. "In finance, an option is a contract which gives the buyer (the owner) the right, but not the obligation, to buy or sell an underlying asset or instrument at a specified strike price on or before a specified date. The seller incurs a corresponding obligation to fulfill the transaction － that is to sell or buy － if the owner elects to "exercise" the option prior to expiration. The buyer pays a premium to the seller for this right. An option which conveys to the owner the right to buy something at a specific price is called a call; an option which conveys the right of the owner to sell something at a specific price is called a put. Both are commonly traded, though in basic finance for clarity the call option is more frequently discussed. ”(Black, Fischer; Myron Scholes (1973))

There are many strategies in option market. In order to obtain an intuitive insight about the impact of fundamental accounting signals on option returns, I choose only a long straddle contract in my research paper, because straddle contract is merely sensitive to the volatility of equity price movement.

“In finance, a straddle is an investment strategy involving the purchase or sale of particular option derivatives that allows the holder to profit based on how much the price of the underlying security moves, regardless of the direction of price movement. The purchase of particular option derivatives is known as a long straddle, while the sale of the option derivatives is known as a short straddle. A long straddle involves going long, i.e., purchasing, both a call option and a put option on some stock, interest rate, index or other underlying. The two options are bought at the same strike price and expire at the same time. The owner of a long straddle makes a profit if the underlying price moves a long way from the strike price, either above or below. Thus, an investor may take a long straddle position if he thinks the market is highly volatile, but does not know in which direction it is going to move. This position is a limited risk, since the most a purchaser may lose is the cost of both options. At the same time, there is unlimited profit potential.” (McMillan, Lawrence G. (2002))

For example, company XYZ is set to release its quarterly financial results in two weeks. A trader believes that the release of these results will cause a large movement in the price of XYZ's stock, but does not know whether the price will go up or down. He can enter into a long straddle, where he gets a profit no matter which way the price of XYZ stock moves, if the price changes enough either way. If the price goes up enough, he uses the call option and ignores the put option. If the price goes down, he uses the put option and ignores the call option. If the price does not change enough, he loses money, up to the total amount paid for the two options. The risk is limited by the total premium paid for the options, as opposed to the short straddle where the risk is virtually

unlimited.



Option payoff diagram for a long straddle struck at K where the total cost of the two constitutent options is V

This graph illustrates that the more the stock price fluctuates, the more payoffs I can obtain from a straddle contract.

1.3 Research Process

This paper is going to investigate the effect of the fundamental accounting signals on the future option returns, which means if the fundamental accounting signals can generate incremental predictive information to obtain significant future option returns.

Specifically, I divide my paper into two steps. First, I would study whether fundamental accounting signals can generate predictive information of extreme stock price movements, and then investigate whether I can obtain significant future option returns based on this information. Because the future option returns is related to the price movements of underlying equity securities.

To start with, I would emphasize three main points of my research. First, I examine the role of fundamental accounting signals in the option market. On one hand, the leveraged essence of option contracts will attract a great deal of investors who want to exploit all the private information. On the other hand, due to some institutional features of option market will somehow make it less efficient. Secondly, I would represent the accounting signals as volatility to do my research. Volatility plays an important role in determining option prices. Furthermore, I focus on one specific option contract: an at-the-money straddle. A straddle contract purchases one call option and one put option, the payoff of this contract is based on the exact price movement of the underlying equity securities. The reason why I choose straddle is that unidirectional relationship between fundamental accounting information and the payoff from the straddle contract.

As for the fundamental accounting signals, I decide to use two groups of information which are implied volatility and historical volatility. Firstly, I would like to pick the fundamental volatility based on the latest information spread out by the company. Meanwhile, I would choose the fundamental volatility recorded through a long period of time. Afterwards, I fix my collection of fundamental information into one single measure of the expected benefits. These measures I record from fundamental signals have their own regular patterns, which have the predictive capacity to future straddle option returns, based on implied volatility and historical volatility. For example, when fundamental volatility is high, implied volatility is low temporarily. Thus, option returns become predictable ex ante.

Moreover, studying the signals related to fundamental volatility in the option market will be able to give a deeper understanding of how investors exploit accounting data than investors use the pricing signals in the equity market. Because I can mitigate the risk of stock expected returns to the returns of option, specifically the straddle contract. The returns of straddle contract are associated basically with the magnitude of stock price movement, regardless of any other volatility. Hence, by testing the relationship between the fundamental accounting signals and the option returns, I can obtain deeper insight about whether investors can exploit the accounting information to get stable expected return in the future.

The rest of my research paper is represented as follows. Chapter 2 will illustrate some review of the literature on implied volatility, straddle strategies, as well as fundamental analysis. Afterwards, in Chapter 3, I would like to provide details of my model and the variable in it. Chapter 4 represents my results. Furthermore, Chapter 5 will make the conclusion and references.

Chapter 2 Literature Review

2.1 Option returns

An increasing number of researches has tested option returns and tried to relate to expected returns and market efficiency. Recently work on option returns focused on the returns to option positions depended on index (e.g., an S&P 100 index call option). For instance, Coval and Shumway (2001) provide a theoretical and empirical analysis of the expected returns related to option positions. They explained that basing on the leveraged nature of an option, call (put) options have higher or lower expected returns than the underlying equity securities due to financial derivatives expose more in risk than stock does. They confirmed these predictions empirical analysis of S&P 100 index options. Additionally, they learn that straddle positions are insensitive to market risk (zero-beta straddles) have negative average returns, compare to the prediction from existing asset-pricing models that these securities should have an expected return identical to the risk-free rate, raising questions about the pricing of these securities.

Nowadays, researchers have investigated the returns from options depended on individual equity securities. For instance, Goyal and Saretto (2009) find that the difference among implied and historical volatility can predict straddle option returns. They announced that implied volatility is inaccurate when it is generated from historical volatility too much, due to volatility will be quickly mean-reverting. At last, straddle contact returns convert to be positive when implied volatility is below historical volatility and negative when implied volatility is over historical volatility. Specifically, option investors are more complex, and according to the literature of Goyal and Saretto (2009), there will be questions about whether option market will be efficiently affected by available fundamental accounting signals (volatility).

Afterwards, few number of recent research works investigate the cross-section of option returns. Choy (2011) gives evidence that a firm's zero-beta straddle positions have more negative returns when retail investors account for a greater proportion of that firm's trading, a finding consistent with retail investor trades resulting in option prices where implied volatility is not a sufficient statistic for future realized volatility owing to behavioral biases. Other papers investigate the determinants of call and put returns, but not straddle returns. We quote these literatures to explore whether option returns can be predicted by accounting-based fundamental accounting signals.

2.2 Accounting signals, volatility, and option returns

A large literature in accounting examines the extent to which investors effectively interpret and price financial accounting information, although this literature has focused on the predictability of future earnings and future stock returns. A number of pape rs have suggested that accounting-based signals or fundamental analysis could generate abnormal returns (e.g., Bernard and Thomas 1990; Sloan 1996; Ou and Penman 1989; Holthausen and Larcker 1992; Abarbanell and Bushee 1998; Piotroski 2000).

On the volatility side, the literature shows that a firm's fundamental volatility determines (although does not fully explain) stock price volatility (Shiller 1981; Scheinkman and Xiong 2003; Paster and Veronesi 2003; Callen2009). The high correlation between fundamental volatility and stock volatility creates the possibility for fundament al analysis to play a role in predicting stock volatility. While much of the literature on financial statement analysis has focused on the prediction of future earnings and future stock returns, research also examines whether accounting measures provide information about future uncertainty or the magnitude of future price movements. In direct relation to our study, Beneish et al. (2001) show that fundamental signals, such as earnings- or sales-based variables, can predict future extreme (either upward or downward) price movements after controlling for market-based signals. Several recent accounting studies have also explored the link between accounting information and option markets with an emphasis on implied volatilities. Rogers, Van Buskirk, and Skinner (2009) find that the implied volatility values increase after managerial forecasts, particularly when the forecast conveys bad news. Dubinsky and Johannes (2006) find that the implied volatility imbedded in a firms options tends to change when an earnings announcement occurs, suggesting that option investors understand the opportunity for a material jump in price at an earnings announcement. Barth and So (2009) explore whether accounting information is associated with the gap between implied volatility and the subsequent realized volatility during an earnings announcement window. They find that firms with losses or more volatile earnings are more likely to have implied volatilities that are higher than the subsequent realized volatilities at the earnings announcement and interpret the difference as a risk premium. None of these papers examines the link between accounting signals and future opti on returns, especially after controlling for market-based signals used in the finance literature. Building on the prior literature on accounting signals and future price volatility, this paper examines the role of fundamental signals in predicting option returns. The financial reporting system produces a rich set of fundamental variables that capture the uncertainty or volatility of a firm' s operation. Historical stock volatility and implied volatility in option contracts may not fully reflect such underlying fundamental volatility, which manifests itself in the future. Similar to Goyal and Saretto (2009) who suggest that option investors under-react to historical volatility (i.e., ignoring the role of historical volatility in a mean reverting process), we posit that option implied volatility may temporarily deviate from fundamental volatility and, as a result, fundamental signals predict option returns. This leads to the central prediction of our paper: historical fundamental signal s predict option returns. In tests of our hypothesis, two issues are important to address, both conceptually and empirically. First, we must show that fundamental signals convey incremental information about future option returns beyond what is captured in historical volatility, which the finance literature has shown to predict option returns. Historical volatility is a noisy measure of a firm's underlying volatility, leaving the room for fundamental volatility to play a role. Second, we must show that predictable option re turns are not due to higher risk borne by option investors.

Chapter 3 Research design and data collection

3.1. The measurement between fundamental signals and stock price movements

In order to design my research, I decide to use two sets of fundamental information to analyze the option returns and I present the fundamental signals as fundamental volatility. As for the first set of information, I use the fundamental volatility in short-term earnings announcement which are represented in sales and earnings. And these informations are used for testing if the accounting signals can significantly influence extreme stock price movements. As for the second set of information, I use the fundamental volatility in long-term earning announcements. So as to eliminate the risk of data mining, I decide to merely consider sales and earnings information. In the short-term measurement, based on the return prediction models (Beneish et NLAMRal. 2001) in the stock market, I can learn that the information about sales growth and earnings performance is positively correlated with the probability that a firm has unidirectional price movement. So I choose to use these four measurements, **SA, CHG, STD_SA, STD_CHG,** to discover the volatility of sales and earnings flows. Meanwhile, in the long-term measurement, based on the same model and the same variables, I discover the volatility of sales and earnings flows identically. At the last step of this part, both volatilities in long-term will be estimated over the same periods as 6 years prior to quarter n. Specifically, I choose four business giants in the US, which are Apple Inc., Google Inc, P&G, Microsoft respectively, to collect the accounting data. These data will be all dated from December, 2004 to June, 2013 quarterly.

3.2. Fundamental signals and option returns

The essence of my research paper is to investigate whether fundamental accounting signals can offer us predictive information about the option returns. Therefore, after getting the signals above, I choose to synthesis them into one single measure which represent the volatilities of sales- and earnings- based in four firms both in short-term and long-term. And then I am going to collect the data of option returns each three months after quarter n and then I calculate the average returns. I focus on the absolute value of monthly returns, because the absolute value is identical to the value that can be realized at the end of the month from the at-the-money straddle contract. Besides, the absolute-value approach follows the research work in Beneish et al (2001).

In order to generate the relationship between fundamental accounting signals and the absolute value of returns, I will match the fundamental accounting signals to the calculated option returns. The fundamental signals are calculated as of every quarterly income statement, which are quarterly sales and net income before extraordinary items. So as to limit the weight on the absolute value of returns, I will use the natural log of the average absolute value and represents this dependent variable as **NLAMR.**

According to introduction above, I can give the model below:

SA=(Sales $_{n}$/Sales $_{n-4}$)-1;

CHG=(IBE $_n$-IBE $_{n-4}$)/MVQ $_{n-4}$, where **IBE**=quarterly income before extraordinary items during quarter n; **MVQ**=market value of equity at the end of quarter n;

STD_SA=natural log of the standard deviation of SA over 6 years;

STD_CHG=natural log of the standard deviation of CHG over 6 years;

NLAMR $_{n+1}$=natural log of the average absolute monthly return over 3 months after the firm's accounting announcements occurs.

$$\mathbf{NLAMR}_{n+1} = \alpha_0 + \alpha_1 \mathbf{SA}_n + \alpha_2 \mathbf{CHG}_n + \alpha_3 \mathbf{STD\_SA}_n + \alpha_4 \mathbf{STD\_CHG}_n + \varepsilon$$

3.3 Analysis procedure

As illustrated above, I separate the independent variables into two groups: variables from the short-term accounting signals at every quarter n (**SA**, **SAN**, **CHG**, and **IBEN**) and variables from long-term accounting signals prior every quarter n (**STD_SA**, **STD_CHG**). The dependent variable, **NLAMR,** is represented as the average absolute value over the three months after the month when sales and net incomes announced at quarter n. Using the following method, I calculate rolling estimates of Equation on the basis of fundamental accounting signals when the firm announces its sales and net incomes.

First, I separate all income statements into groups depend on the year and calendar quarter when the revenue accrued. For each calendar quarter n, I estimate Equation using historical data which are available at the end of that quarter. I limit this sample to income statement through the two years before that calendar quarter. Afterwards, I analyze the coefficients for Equation estimated using historical data and apply them to the current period’s fundamental signals to obtain a predicted value (E [NLAMR]).

For example, a firm reporting earnings during March of 2012 would be recognized to the initial calendar quarter of 2012. As for this quarter, I generate a sample to calculate Equation by using data available before January 1, 2012. The sample will include four firms (Apple Inc., Google Inc, P&G) that reported sales and net incomes after January 1, 2010 and before December 30, 2011. This date range makes sure that three months of returns following the sales and incomes announcement (I need to calculate the NLAMR through the data I collect) are also observable before March 1, 2012. The coefficients from this equation will be examined according to the signals available at the sales and incomes announcement during March 2012, which would then be used to estimate straddle returns in April, May and June 2012. I study my analysis of fundamental accounting signals by regressing the Equation with four firms where I have sufficient data to estimate the fundamental signals both in short-term and long-term to calculate the average absolute value of monthly returns in the three months after the sales and incomes announcement.

Before estimating Equation, I would like to request the following sample collection and calculation criteria. Firstly, I require that each firm has non-missing Compustat data on the market value of equity and book value of equity at the end of quarter n. To limit the influence of outliers during the estimation period, every original data of the dependent and independent variables are normalized in each sample before estimating Equation. As we examine option returns that occur between December 2007 and June 2011, I estimate 72 versions of Equation covering rolling windows from the first calendar quarter of 2007 through the second quarter of 2011. In order to make my analysis significant, I am going to test if the data is stationary. I will use the Augmented Dickey－Fuller unit-root test.

Chapter 4 Results

According to the analysis procedure I described in Chapter 3, I use the time series data of four sample companies to analyze the relationship between fundamental accounting signals and option returns. However, if I choose to use the time series data, I need to test whether the data is stationary. Therefore, I use Dickey-Fuller test for unit root and the results of the test are as follow.

Apple Inc.	**Test Statistic**	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**	**P-Value**
SA	-1.106	-3.750	-3.000	-2.630	0.7127
CHG	-1.982	-3.750	-3.000	-2.630	0.2944
STD_SA	-0.727	-3.750	-3.000	-2.630	0.8395
STD_CHG	0.919	-3.750	-3.000	-2.630	0.9933
NLAMR	0.485	-3.750	-3.000	-2.630	0.9844

Microsoft	**Test**	**1% Critical**	**5% Critical**	**10% Critical**	**P-Value**

Corp.	Statistic	Value	Value	Value	
SA	-2.749	-3.750	-3.00	-2.630	0.0659
CHG	-2.394	-3.750	-3.00	-2.630	0.1436
STD_SA	-0.650	-3.750	-3.00	-2.630	0.8592
STD_CHG	-0.128	-3.750	-3.00	-2.630	0.9466
NLAMR	-0.945	-3.750	-3.00	-2.630	0.7729

Google Inc.	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	P-Value
SA	-2.301	-3.750	-3.000	-2.630	0.1717
CHG	-2.654	-3.750	-3.000	-2.630	0.0824
STD_SA	-0.468	-3.750	-3.000	-2.630	0.8981
STD_CHG	-2.085	-3.750	-3.000	-2.630	0.2506
NLAMR	-1.557	-3.750	-3.000	-2.630	0.5053

P & G	**Test Statistic**	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**	**P-Value**
SA	-1.447	-3.750	-3.000	-2.630	0.5598
CHG	-5.128	-3.750	-3.000	-2.630	0.0000
STD_SA	-2.085	-3.750	-3.000	-2.630	0.2508
STD_CHG	-1.828	-3.750	-3.000	-2.630	0.3666
NLAMR	-2.317	-3.750	-3.000	-2.630	0.1664

According to the results of the Dickey-Fuller test, I can see that the P-value of both independent variables and dependent variables are larger than 0.05, which means all the time series data of four sample companies are non-stationary.

In mathematics, a stationary process is a stochastic process whose joint probability distribution does not change when shifted in time or space. Consequently, parameters such as the mean and variance, if they are present, also do not change over time or position. As a result, the mean and the variance of the process do not follow trends.

Using non-stationary time series data in financial models produces unreliable and spurious results and leads to poor understanding and forecasting. The solution to the problem is to transform the time series data so that it becomes stationary. If the non-stationary process is a random walk with or without a drift, it is transformed to stationary process by differencing. On the other hand, if the time series data analyzed exhibits a deterministic trend, the spurious results can be avoided by detrending. Sometimes the non-stationary series may combine a stochastic and deterministic trend at the same time and to avoid obtaining misleading results both differencing and detrending should be applied, as differencing will remove the trend in the variance and detrending will remove the deterministic trend. Hence, I need to eliminate the non-stationary condition and then do the regression. The following sheets are the results of the regression:

Apple Inc.

Source	SS	df	MS
Model	.008053449	4	.002013362
Residual	.000595948	8	.000074494
Total	.008649397	12	.000720783

Number of obs	=	13
F(4, 8)	=	27.03
Prob > F	=	0.0001
R-squared	=	0.9311
Adj R-squared	=	0.8966
Root MSE	=	.00863

D.nlamr	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sa D1.	.0175935	.0180982	0.97	0.359	-.0241411	.0593281
std_sa D1.	.076024	.0441471	1.72	0.123	-.0257794	.1778274
chg D1.	-.0218939	.0281307	-0.78	0.459	-.0867635	.0429757
std_chg D1.	.8059761	.0841086	9.58	0.000	.6120212	.999931
_cons	-.0007418	.0027501	-0.27	0.794	-.0070835	.0055999

Microsoft Corp.

Source	SS	df	MS
Model	.00077517	4	.000193793
Residual	.000408547	8	.000051068
Total	.001183717	12	.000098643

Number of obs	=	13
F(4, 8)	=	3.79
Prob > F	=	0.0514
R-squared	=	0.6549
Adj R-squared	=	0.4823
Root MSE	=	.00715

D.nlamr	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sa D1.	-.0263003	.0333125	-0.79	0.453	-.1031191	.0505184
std_sa D1.	-.2097786	.1460848	-1.44	0.189	-.5466508	.1270935
chg D1.	.2316222	.2142974	1.08	0.311	-.2625485	.7257929
std_chg D1.	4.937105	1.489674	3.31	0.011	1.50191	8.372299
_cons	.0017363	.002104	0.83	0.433	-.0031157	.0065882

Google Inc.

Source	SS	df	MS
Model	.001633297	4	.000408324
Residual	.000353207	8	.000044151
Total	.001986504	12	.000165542

Number of obs	=	13
F(4, 8)	=	9.25
Prob > F	=	0.0043
R-squared	=	0.8222
Adj R-squared	=	0.7333
Root MSE	=	.00664

D.nlamr	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sa D1.	.0192459	.0219648	0.88	0.406	-.031405	.0698967
std_sa D1.	-.120357	.0652188	-1.85	0.102	-.2707518	.0300377
chg D1.	.0446815	.0722667	0.62	0.554	-.121966	.2113289
std_chg D1.	1.196734	.2564131	4.67	0.002	.6054443	1.788024
_cons	-.0005268	.0019452	-0.27	0.793	-.0050125	.003959

Procter & Gamble

Source	SS	df	MS
Model	.001322318	4	.00033058
Residual	.0001086	8	.000013575
Total	.001430918	12	.000119243

Number of obs	=	13
F(4, 8)	=	24.35
Prob > F	=	0.0002
R-squared	=	0.9241
Adj R-squared	=	0.8862
Root MSE	=	.00368

D.nlamr	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sa D1.	.0019904	.0227615	0.09	0.932	-.0504978	.0544786
std_sa D1.	.03632	.0654388	0.56	0.594	-.1145821	.187222
chg	-.037289	.129896	-0.29	0.781	-.3368296	.2622516
std_chg D1.	2.928483	.3518193	8.32	0.000	2.117186	3.739779
_cons	.0002311	.0011845	0.20	0.850	-.0025003	.0029626

After regressing the data, I need to check whether the independent variables are significant, which means that the specific variable has significant influence on the dependent variable. Firstly, I focus on the value of R-squared. Observing all the R-squared of four regression results, I can see that the value of R-squared are 0.9311, 0.6549, 0.8222, 0.9241 respectively, which means the four regression models have high fit statistics. Secondly, according to the P-value of every regression result from four sample company, there is only one significant variable out of four independent variables. The P-value of STD_CHG are all less than 0.05, which means STD_CHG has significant influence on NLAMR. I would like to choose Apple Inc. to be an example. The P-value of STD_CHG from Apple Inc. is 0.0000, which is way less than

0.05 and the t-value of STD_CHG is 9.58, which is way larger than 2. Therefore, STD_CHG has significant influence on NLAMR. The coefficient of STD_CHG is 0.8059761, which means if the STD_CHG has one unit up movement, there will be 0.8059761 unit up movement of NLAMR. Hence, based on the result of all regression, I believe that STD_CHG has a strong and positive correlation with NLAMR.

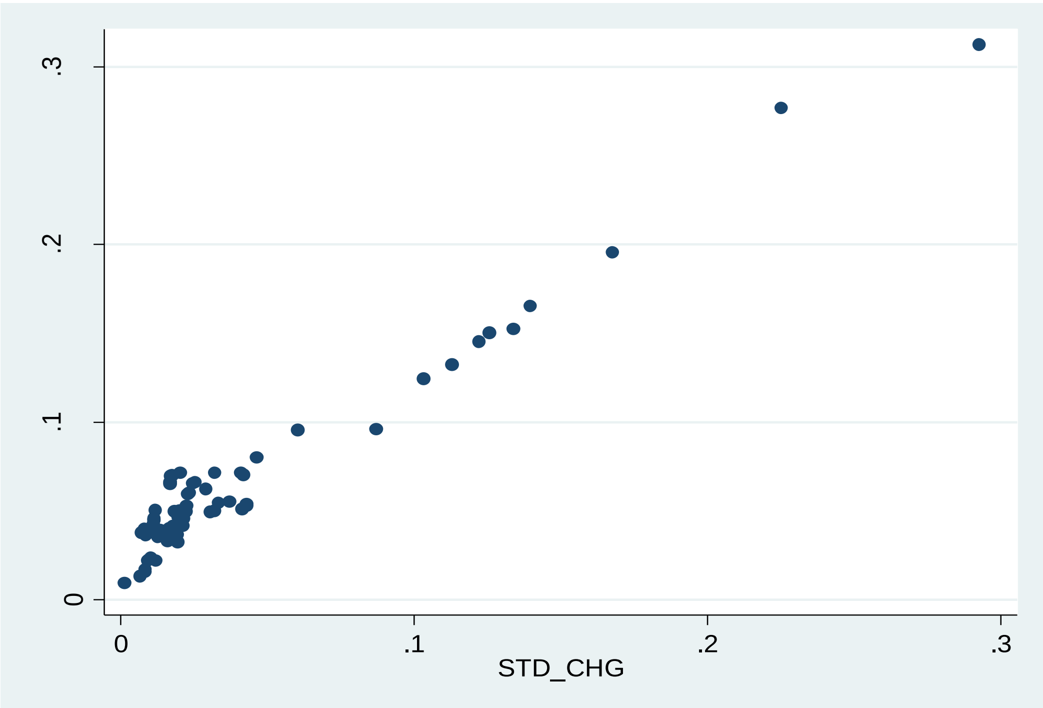
Based on the analysis above, I would like to eliminate the time series and investigate the relationship among all four independent variables, SA, CHG, STD_SA, STD_CHG and NLAMR. I use the same equation which I present in Chapter 3 to do the regression and the results are as follow:

Source	SS	df	MS
Model	.19451974	4	.048629935
Residual	.008290771	67	.000123743
Total	.202810511	71	.002856486

Number of obs	=	72
F(4, 67)	=	392.99
Prob > F	=	0.0000
R-squared	=	0.9591
Adj R-squared	=	0.9567
Root MSE	=	.01112

nlamr	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sa	.000248	.0091956	0.03	0.979	-.0181064	.0186025
std_sa	-.0687149	.0269439	-2.55	0.013	-.1224952	-.0149346
chg	-.0096656	.0170831	-0.57	0.573	-.0437637	.0244325
std_chg	1.073146	.0353103	30.39	0.000	1.002666	1.143625
_cons	.0321505	.0027487	11.70	0.000	.0266641	.0376368

Based on this regression result, I can see that the value of R-squared is 0.9591 which means the regression model has high fit statistics. Furthermore, I focus on the P-value of STD_CHG which is 0.0000. It means that STD_CHG is significant and it has strong positive relationship with NLAMR. The coefficient of STD_CHG is 1.073146, which means one unit of STD_CHG up movement, NLAMR will have a 1.073146 unit of up movement. Therefore, I believe that STD_CHG has a strong and positive relationship with NLAMR. Moreover, based on the positive correlation between NLAMR and STD_CHG , I made a scatter graph below. According to the graph below, I can see that the independent variable STD_CHG and dependent variable NLAMR has strong and positive relationship.



Chapter 5 Conclusion

In my research work, I obtain the conclusion that option return is strongly and positively correlated with the standard deviation of quarterly net income volatility, which is based on the regression between fundamental accounting signals and the option returns. At the beginning of my research, I represent the fundamental accounting signals as long-term and short-term sales volatility, and I choose the straddle contract to calculate the option return. Because the return of straddle contract is merely correlated with stock price volatility and the stock price volatility is strongly influenced by the fundamental accounting signals. Based on this conclusion, I strongly recommend that investors could focus on the volatility of the fundamental accounting signals to obtain a certain option returns, because the more volatile the accounting signals are, the more profits the investors can obtain.

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(In Million)						
Apple Inc.	Date	SA	STD_SA	CHG	STD_CHG	NLAMR
	Jun. 28th,	0.008565799617394	0.308008072884446	-0.123547164965004	0.292720372	0.312568
	Mar. 28th,	0.112718828152912	0.292676052778556	-0.139730639730640	0.225284773	0.276895
	Dec. 31th,	0.176526449830574	0.225318008724353	0.001002793496168	0.167826806	0.195678
	Jun. 29th,	0.225823387350810	0.106224847543652	0.119229256783327	0.133938345	0.152465
	Mar. 30th,	0.588600154051972	0.086845882602779	0.457163718968035	0.139741568	0.165235
	Dec. 31th,	0.732657716614936	0.128172227532542	0.613806294557468	0.060366653	0.095684
	Jun. 30th,	0.819808917197452	0.275554584660291	0.400177637422284	0.103222796	0.124578
	Mar. 31th,	0.827320542262390	0.326145838215849	0.304930388359678	0.122195589	0.145268
	Dec. 31th,	0.705094688516228	0.350052107778211	0.293014952019638	0.125656056	0.150231
	Jun. 30th,	0.883171404581984	0.255937126767243	0.254367223828076	0.112897013	0.132585
	Mar. 31th,	0.653681244640451	0.206328838802651	0.244537485280649	0.087119317	0.095874
	Dec. 31th,	0.542539588865939	0.166322470746053	0.239853896103896	0.042847586	0.052631
	Jun. 30th,	0.116961414790997	0.155942978568448	0.022983457766067	0.042855986	0.053654
	Mar. 31th,	0.086661341853035	0.136131916851407	0.025228634500158	0.041336707	0.051248
	Dec. 31th,	0.058180682764363	0.090587301017283	0.003969566655640	0.030492244	0.049563
	Jun. 30th,	0.379667282809612	0.085770172218125	0.049329966983880	0.03211349	0.050124
	Mar. 31th,	0.427051671732523	0.061214362132229	0.056724422442244	0.037081051	0.055236
	Dec. 31th,	0.350386507378777	0.167332707850180	0.125598606878537	0.033300569	0.054312
Microsoft Corp.	Date	SA	STD_SA	CHG	STD_CHG	NLAMR
	Mar. 31th,	0.177055207675073	0.069616192036202	0.014508295926340	0.012904194	0.036254
	Dec. 31th,	0.027340196313144	0.069175333700211	-0.003865293731026	0.012784173	0.035263
	Sep. 30th,	-0.078517154040986	0.080524441323423	-0.020034020034020	0.012946203	0.037654
	Mar. 31th,	0.059593377160945	0.080209192002425	-0.001960970364045	0.012099698	0.021856
	Dec. 31th,	0.046709767954694	0.076320315406303	-0.000162216526620	0.015124099	0.036598
	Sep. 30th,	0.072676752083977	0.132299415085788	0.005295874707354	0.019514062	0.046598
	Mar. 31th,	0.132731159070537	0.140337911304707	0.019610665898876	0.02457069	0.065324
	Dec. 31th,	0.048943328777206	0.141115999349252	-0.000447527411054	0.025366757	0.065987
	Sep. 30th,	0.253482972136223	0.104647319295949	0.029473616618240	0.02289343	0.059512
	Mar. 31th,	0.062646541617820	0.102568770592594	0.016624660721210	0.022089917	0.049887
	Dec. 31th,	0.143905225810331	0.153194587087827	0.040526452958040	0.019622949	0.048799
	Sep. 30th,	-0.142155235376137	0.149863222629143	-0.012959208498905	0.019941089	0.049988
	Mar. 31th,	-0.055763110557631	0.147384542151261	-0.022264299802761	0.019349432	0.032519
	Dec. 31th,	0.016007820614652	0.139196309283003	-0.008524181166837	0.021275102	0.045655
	Sep. 30th,	0.094390350239791	0.137514384475090	0.001383877823358	0.021030084	0.041322
	Mar. 31th,	0.003889429087373	0.112514163970826	-0.008844756440397	0.0190865	0.036556
	Dec. 31th,	0.304975283048956	0.105980945174818	0.034029958137101	0.016108697	0.034421
	Sep. 30th,	0.272962723152345	0.097977544308525	0.014065941689647	0.01589539	0.033123
Google Inc.	Date	SA	STD_SA	CHG	STD_CHG	NLAMR
	20112	0.154822335025381	0.068015238947466	0.020742613662968	0.029147998	0.062395
	20111	0.312259276655707	0.073669307295540	0.021928348160616	0.032080211	0.071325
	20104	0.450720164609054	0.053214278599760	-0.028075341422552	0.023160053	0.060032
	20103	0.353201861289608	0.046915998946998	0.014571190674438	0.022389727	0.052612
	20102	0.241399416909621	0.048580043362211	0.058072750478622	0.018208288	0.049652
	20101	0.334065330771342	0.083186417247757	0.032234012044738	0.017942771	0.041326
	20094	0.323460410557185	0.099068552646346	0.038868431819510	0.016645245	0.040221
	20093	0.265682656826568	0.097152450570416	-0.009708737864078	0.010400233	0.023655
	20092	0.225567703952902	0.115809379145766	0.034265279583875	0.009336296	0.021998
	20091	0.234836139779106	0.148223823689452	0.023597447487370	0.009473588	0.022089
	20084	0.229805772372481	0.176881100471964	0.036202790064648	0.006703582	0.013321
	20083	0.072911026890453	0.212173980756161	0.024658306326617	0.008484082	0.016998
	20082	0.029066517607602	0.191158933304363	0.017117376294592	0.008286094	0.015699
	20081	0.062283069803317	0.127392745220766	0.008553310721133	0.013245998	0.039065
	20074	0.309619475301347	0.123114628327976	0.017145974592783	0.01378243	0.038997
	20073	0.386105371900826	0.123810281311584	0.025602289894252	0.041749932	0.070215
	20072	0.415393013100437	0.097288299724017	0.024975433999345	0.040904794	0.071325
	20071	0.572862453531599	0.136811442837435	0.032750242954325	0.046327208	0.080021
P & G	Date	SA	STD_SA	CHG	STD_CHG	NLAMR
	2013.3	0.020005942359117	0.050051428896200	0.002351727381693	0.020238959	0.071325
	2012.12	0.001807092839395	0.049305585272882	0.036471494607088	0.01142915	0.045699
	2012.9	-0.053748231966054	0.032999515215925	-0.003199561203035	0.01141325	0.045122
	2012.3	-0.001779535343549	0.027632961076312	-0.006851346541701	0.011894026	0.050325
	2011.12	0.036913852063522	0.027870252233556	-0.025389025389025	0.008071529	0.039887
	2011.9	0.089205844349468	0.056247453499254	-0.000901884463853	0.008094018	0.039589
	2011.3	0.054854520805089	0.066108129051189	0.004313120572687	0.007184451	0.037852
	2010.12	0.015218528558520	0.065772258388938	-0.019232163835990	0.011466047	0.044951
	2010.9	0.015903468470743	0.080974282947513	-0.003371775553135	0.01112168	0.042596
	2010.3	0.041320519085627	0.090777102835061	-0.000460715754833	0.010960319	0.040753
	2009.12	0.032354673998429	0.099122763078346	-0.005527783118631	0.009885471	0.038526
	2009.9	-0.100744574593662	0.087381048889948	-0.000635048480530	0.009338457	0.037426
	2009.3	-0.099985339393051	0.059036715495215	-0.001393898460964	0.008517812	0.036258
	2008.12	-0.055944380069525	0.008723209503638	0.025409199478335	0.001221203	0.009251
	2008.9	0.090450022278331	0.076087404149101	0.003981704880179	0.01682617	0.065963
	2008.3	0.094629292821226	0.083471483677539	0.002978966689736	0.017070713	0.069842
	2007.12	0.093789607097592	0.096115745184037	0.006241968055811	0.016757417	0.064967
	2007.9	0.075272824061751	0.095923584176673	0.005970570259978	0.01752163	0.070153