THE RELATIONSHIP BETWEEN OP/OS RATIO AND ABNORMAL RETURN

by

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Abstract

Trading volume in options may either be a positive or negative signal for future performance. First, if investors trade options because of increased risk, one may think that high option trading should be associated with a higher return. Second, if option trading reflects the degree of informed trading associated with the firm, then again investors should require a higher return on average for shares that have high option trading. Third, option trading can potentially quantify the degree of short sale constraints. According to this third hypothesis, options are used to bypass short-selling constraints. This suggests that informed traders expect a reduction in prices, which should be reflected in lower returns. I find that shares that have the lowest option trading volume outperform the highest one by 0.22% per day.

Keywords: Option; Trading volume ; Informed Trading; Abnormal return

Dedication

I would like to give my great thankfulness to my friends and families who support me selflessly during this process.

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1. Introduction

The increasing availability of derivatives makes it a hot topic for research in recent decades. If the market were actually perfect, options are redundant securities as they can be replicated by a portfolio of risk free bonds and stocks (Black and Scholes 1973). However, it seems like market frictions (e.g., short sale constraint, transaction costs, information asymmetry) lead to imperfect markets, in which options play an important role in price recovery. Options allow traders to take advantage of leverage and align their strategies with the sign and magnitude of their information. Informed traders may prefer to trade in option markets rather than in stock markets to magnify their benefits. In other words, one can argue that options can potentially quantify the degree of informed trading activity. Furthermore, trades in the options market may have stronger signals than trades in stock markets, and can potentially be predictive of an abnormal return.

In this paper, I will discuss the relationship between the option trading volume and the abnormal returns of the stocks. In order to lessen the influence of a firm's size, the OP/OS ratio is used rather than the absolute number of trading volume in options market. The OP/OS ratio is defined as the option trading volume divided by the number of outstanding shares. This ratio can mitigate the influence of firms' size and provide clear information about the relative trading volume in option and stock market.

My data analysis procedure can be briefly summarized as follow. First, I merged the annual options and stock data for 2003 to 2013 to calculate the OP/OS Ratio. Second, I sorted the data by OP/OS ratio and divided it into 10 portfolios by firm-days based on OP/OS ratio. Then for every year, each portfolio was sub-divided and arranged, by OP/OS Ratio, into 10 ascending sub-portfolios. After this, I did a vertical merge of data for the 11 years and sort the data by portfolio number. For this final data sample, there are 10 portfolios, and each portfolio has 11 sub-portfolios; for example, portfolio one consists of 11 sub-portfolio ones from every year from 2003 to 2013. After these steps, the portfolio one will have the lowest OP/OS ratio on average and the portfolio ten will have the highest OP/OS ratio on average. To get the abnormal return, I used the Fama-

French four-factor model and regressed each portfolio. Based on my results, the portfolio with lowest OP/OS ratio outperformed the portfolio with the highest OP/OS ratio.

One innovation in my paper is the analysis about the property of OP/OS ratio. I explored the relation between the OP/OS ratio and market capitalization and analyzed the OP/OS ratio for each major industry. Moreover, I used the OP/OS ratio, which is the option trading volume divided by the number of share outstanding, rather than the O/S ratio, which was used as a measurement in earlier paper.

The rest of the paper is outlined as follows. Section 2 will discuss the theoretical background and expand on the main hypothesis. Section 3 describes data and methodology. Section 4 provides results and Section 5 concludes the thesis.

2. Literature review

Since the market is not perfect, options can't be replicated by bonds and stocks and they play an important role in helping to complete the market (Ross,1976, Hakansson, 1982, and Detemple and Selden, 1991). Moreover, options also give traders incentives to trade on private information on the underlying assets. Biais and Hillion (1994) argue that informed traders may prefer to trade on the option market instead of the stock market because of the increased benefit provided by leverage. In 1999, Cao published his paper named "The effect of derivative assets on information acquisition and price behavior in a rational expectations equilibrium". In this paper, he found that traders with information about future contingencies should be able to trade more effectively on their information in the presence of options, thus improving informational efficiency. Cao and Wei (2008) gathered evidence from option market and showed that the problem of information asymmetry is more serious in option market than it is in stock market, implying that for traders with private information, option market is a more efficient venue to trade.

Consistent with the preceding notions, Poteshman and Pan (2006) examine the informational content of option trading for future movements in underlying stock prices. From their findings, we can see the option trading volumes contain information about future potential stock prices. Ni, Pan, and Poteshman (2008) showed that options order flows forecast stock volatility.

The findings of those listed above have generally supported the notion that trades in the options market can be used as a predictive signal in the stock market. There are three papers which address the similar issue in my paper, their authors are Easley, O'Hara, and Srinivas (1998), Roll, Schwartz, and Subrahmanyam (2009) and Johnson and So (2012).

Easley, O'Hara, and Srinivas (1998) did the research about the option volume and stock price. They developed an asymmetric information model which showed informed traders can trade in both options and stock markets. Under this condition, option trades should have an effect on the subsequent behavior of stock markets since traders can learn the information from both markets. They used option data for October and November 1990 and found that option markets are a venue for information-based trading, and both negative and positive option volume can be used as predictive signal for stock price movements.

Roll, Schwartz, and Subrahmanyam (2009) did their research because little was known about what drives volume in derivatives relative to their underlying equities. Their paper was the first attempt at addressing the unknown issue. In their paper, RSS used O/S ratio, which is the trading volume of option divided by trading volume of stock, to measure the relative trading volume in options and stock. Their analysis covered 12 years (from 1996 to 2007) using a comprehensive cross-section and time-series of data on equities and listed options to study the time-series properties and the determinants of an O/S ratio. They found that O/S ratio cross sectionally depended on various determinants such as the costs of trading, the size of the firm, the available degree of leverage in options, institutional holdings, and can be viewed as proxies for the likely availability of private information to some extent. In their research, they also showed that O/S ratio increases significantly in the few days around an earnings announcement. Based on this finding, they came to the conclusion that informed traders believe they possess relevant information about the upcoming event, they appear to affect prices, in that high O/S ratio in conjunction with high cumulative abnormal return before earnings announcements.

Similar to the study of Roll, Schwartz, and Subrahmanyam (2009), Johnson and So (2012) also used O/S ratio to measure the relative trading volume in options and stock. Their study focused on the information content of trading volumes, and further explained the conclusion in RRS's paper by showing that option market is more attractive venue for informed traders. Firms with low O/S ratio outperformed the ones with high O/S ratio in terms of future returns.

In their paper, Johnson and So (2012) developed an informed trading model in both equity and options markets in the presence of short-sale costs. They examined the information content of option and equity volumes when agents are privately informed but trade direction is unobserved. Their sample for study covered the period from 1996 to 2010 whereby abnormal return was calculated for 10 portfolios of equally divided firms of descending weekly average O/S ratios. Their findings can be summarized to three general points. First, there is negative relation between O/S ratio and future return. Second, when short sale costs are high, the relation between O/S ratio and future return is stronger. Third, when the option leverage increases, the relation between O/S ratio and future return will decrease. To test the robustness, they also did the time-series analysis for each firm to show that the results were not driven by static firm characteristics correlated with O/S ratio and abnormal returns.

3. Data and methodology

3.1 Data

I used Option Metrics to provide the data used in my analysis. This database is a comprehensive source of historical price and implied volatility data for US equities and index options markets. I got the daily trading volume of total call and put options on equity each year from January 1st 2003 to August 31 2013 in the entire database. Since only actively traded options are of concern, those options trading at a volume of zero were deleted. Table 1 shows the option sample characteristics.

The stock data came from CRSP. This database provides daily stock files for my study. To match the stock with options, I extracted all firms' cusip from the option file and used it to get the daily stock files accordingly. The stock sample includes sic, permno, cusip, date, price, number of shares outstanding and holding period return. For firms which showed missing values in holding period return for certain days, I deleted them so that the result of regression wouldn't be influenced.

To match data in option sample and stock sample, I created a unique id which is the combination of the cusip of the firm and the date of trade; for example "149123102013710", the beginning of id "14912310" is the cusip, the rest of the id "2013710" means July 10, 2013 .I merged option sample with stock sample on yearly base using this unique id and generate OP/OS ratio each day for each stock by dividing the number of option trading volume with number of share outstanding. There is one thing I need to point out is that, the number of share outstanding I used to calculate the OP/OS ratio is in thousand. To clarify, if the OP/OS ratio shows 1000 in my paper, this means that the option trading volume equal the number of share outstanding. In general, the observations of stock sample are larger than that of option sample because of I extract the name from the option sample and get all data of those firms' stock accordingly. For example, if option on Firm A's stock has only been trade for one day in January 2003, I extract the name of firm A and search it in CRSP. The stock sample I get may include 31 days of data because the stock of firm A is traded actively every day. For this reason, there are some missing values of OP/OS ratio. I deleted those missing value and divide the rest of the merged data sample evenly for firm-days into ten portfolios based on ratio for each year. So for every year, there are 10 portfolios, I will call these sub-portfolios. And after I get these 10 sub-portfolios for every year, I merge the yearly data vertically. So the portfolio one consists of sub portfolio 1 for every year, and so do other portfolios. Since I divided the whole sample evenly using firm-days, so that not each firm has observations in all portfolios. After doing this, the portfolio one will have the lowest OP/OS ratio on average and the portfolio ten will have the highest ratio on average. There is a few observations difference in some portfolios because they can't be evenly divided and the Stata made adjustment automatically. Since there are many stocks in every portfolio, I used the equally-weighted average return for each portfolio to the regression.

To get the abnormal return, I use Fama French four factor model. I get the daily factor data (Rft, MKTRF, SMB, HML, UMD) from Fama French & Liquidity Factors database.

My sample data covers the period from 2003 to 2013. I only used part of data for 2013 because the most recent data in Option Metrics ends in August 2013. My choice of data was based on the fact that the tax rate on capital gains is higher than the tax on dividends in the U.S. before 2003, causing some investors to sell to avoid the dividend and others to buy the stock to capture the dividend. However, between 2003 and 2013 these two tax rates became equal at 15% (Bush's tax cuts).The equal tax rates on capital gains and dividends helped us to mitigate concerns that exposure to other forms factors explains the OP/OS ratio-abnormal return relation.

3.2 Methodology

The purpose of this paper is to find the relationship between OP/OS ratio and abnormal return. There are generally two models to get the abnormal return, which are Capital Market Pricing Model and Multiple Factor Model. I will discuss them in detail later. Before using model to get the abnormal return, I did some analysis about the option trading volume and OP/OS ratio.

Figure 1 shows the option volume trend from 2003 to 2013.There is an increasing trend from 2003 to 2011, and the option trading volume reaches its highest level 4110.86 million in 2011.It shows a little decrease from 2011 to 2012. The low option volume shows in 2013 partly because that 2013 contains 8 months of data rather than the whole year. In general, the trend consists with my expectation that the option markets are more active during the recent years.

In addition to the option volume trend analysis, I did the trend analysis for OP/OS ratio as well. Figure 2 shows the trend of OP/OS ratio from 2003 to 2013. The numbers used in this figure come from table 3 column two, the mean of OP/OS ratio of each year. Figure 2 shows a decreasing trend in OP/OS ratio from 2003 to 2007, and an increasing trend from 2008 to 2013.The OP/OS ratio increases faster from year 2011 to 2013 than year 2008 to 2010.

From the trends in figure 1 and figure 2, we can see that from 2003 to 2008, although the option trading volume increases, the OP/OS ratio decreases. This means that although there are more trading in option market, the increase in stock market is even faster. However, after year 2011, the OP/OS ratio increases pretty fast although the absolute option trading volume decreases. This indicates that more investors become aware of the benefit provided by option markets and choose to trade in option markets rather than stock markets.

Before calculating the abnormal return, I summarized the OP/OS ratio by year and as a whole. Table 2 shows the results. The annual average OP/OS ratio is 3,274.52 with a relative high standard deviation of 16189.36. The minimum OP/OS for the whole sample is 0.00649 and the maximum one is 3,902,677.

Table 3 shows the statistical characteristic OP/OS ratio of each portfolio. From this table, we can see that the mean of OP/OS ratio increase from portfolio one to portfolio ten. There is a big difference of 25003.41 in mean between portfolio one and ten.

In order to explore the relation between OP/OS ratio and the market capitalization, I summarized the market capitalization for each portfolio. Table 4 shows the market capitalization characteristics of 10 portfolios. From table 4, it seems that there is no special relation between market capitalization and OP/OS ratio, since the market capitalization doesn't show ascending or descending order from portfolio 1 to portfolio 10. To take one step further, I divided the entire sample into two portfolios based on market capitalization. Table 5 shows the results. From this table, one can argue that portfolio with low market capitalization has lower average OP/OS ratio than the one with high market capitalization. Table 5 also shows the result of two sample T-test, the result indicates that the mean of OP/OS ratio for these two portfolios are different.

Considering that there may be some differences across industry for OP/OS ratio, I made a summary of OP/OS ratio by major industry. Table 6 shows the result. From this table, we can see that manufacturing firms constitute the largest portion of the entire sample. The biggest OP/OS ratio shows in the transportation, communications, electric, gas and sanitary service industry and the smallest one shows in mining industry.

After the above analysis of OP/OS ratio, the next step is choosing a model to calculate abnormal return, which is also called alpha. As mentioned in the beginning of this section, there are generally two models to get the abnormal return, which are Capital Market Pricing Model and Multiple Factor Model.

3.2.1 CAPM

The Capital Asset Pricing Model was introduced in the 1960s by William Sharpe (1964), Jack Treynor (1962), John Lintner (1965) and Jan Mossin (1966). The main characteristic of the CAPM is that only one risk should affect the required return and that is the security's co-movement with the market. The risk premium per unit of riskiness is the same across all assets.The expected return for a security is based upon the risk-free rate and the security's beta. A security that moves in the same direction as the market has a positive beta. A security that moves in the opposite direction of the market has a negative beta. The magnitude of co-movement with or against the market determines beta.

One of the earliest empirical studies of CAPM is made by Black, Jensen and Scholes (1972).They estimated betas by regressing historical returns on a proxy for the market portfolio. Their predictions of the slope and the intercept of their regression line are significantly different from the CAPM predictions. This indicates that the CAPM model fail to capture some risk factors that have influence on the return of the security.

3.2.2 Factor Model

The general reaction to the lack of empirical support for the CAPM has been to focus on other asset pricing models. The Fama–French three-factor model is a model designed by Eugene Fama and Kenneth French to describe stock returns. In contrast to CAPM, the Fama–French model uses three variables.

$$r = R_f + \beta^*(K_m - R_f) + b_s^*SMB + b_v^*HML + \alpha$$

Here r is the portfolio's expected rate of return, R_f is the risk-free return rate, and K_m is the return of the market portfolio. *SMB* stands for "**S**mall [market capitalization] **M**inus **B**ig" and *HML* for "**H**igh [book-to-market ratio] **M**inus **L**ow"; they measure the historic excess returns of small caps over big caps and of value stocks over growth stocks. Other letters in this equation are coefficients for each factor.

Carhart four factor model is an extension of Fama-French three factor model. It has one more factor called momentum factor, also known in the industry as the MOM factor. Momentum in a stock is described as the tendency for the stock price to continue rising if it is going up and to continue declining if it is going down. This Four-Factor model is called Carhart four factor model or Fama-French four factor model. I use this model in this paper to get the abnormal return by doing regression for each portfolio. The formula used is as follow:

$$Rpt - Rft = \alpha + b^*MKTRF + s^*SMBt + h^*HMLt + m^*UMDt$$

Rpt is Daily holding period return for stocks. Rft is Risk-Free Return Rate (One Month Treasury Bill Rate). MKTRF is Excess Return on the Market. SMBt is Small-Minus-Big Return. HMLt is High-Minus-Low Return. UMDt is Momentum Factor.

4. Result

To get the abnormal return of each portfolio, I did 10 regressions for the entire sample data, which is one regression for one portfolio. Since there are many stocks in each portfolio, I used the equally-weighted average to get the return for each portfolio. Table 7 shows the regression result. In general, the t-statistic and p values are statistical significant. The constants show in table 7 are the abnormal returns of each portfolio. The abnormal return shows a decreasing trend from portfolio one to portfolio ten, which is consists with my expectation.

In order to get a more clear idea about the relationship abnormal return and OP/OS ratio, table 8 shows the average OP/OS ratio and abnormal return of 10 portfolios. This table gives me the most important information of this paper. We can see that there is an obvious decreasing trend in abnormal return from portfolio one to portfolio 10, the difference in abnormal return between portfolio one and portfolio ten is 0.0021914, which can be interpreted as the portfolio with lowest OP/OS ratio outperform the highest one by about 0.22% per day.

To test the robustness of this result, I did the two T-tests for abnormal return. Table 9 shows the results. The first T-test is to test the mean of abnormal return of portfolio one and ten. The second T-test is to test the mean of abnormal return between portfolio 2 and portfolio 9. The T-tests are based on the monthly alpha. To get the monthly alpha, I separate the entire sample by month. For each monthly data, there are stocks from different portfolios which I classified before. And then I sort the monthly data by portfolio number and did the regression for portfolio one,two,nine and ten. The return I used for regression is the equally-weighted average return for each portfolio. From January 2003 to August 2013, there are totally 128 months, so the “Obs” column shows 128 observations. The null hypothesis for the T-test is: the mean of two samples are same. Since p value of both T-test equal zero, we can reject the hypothesis that the mean of two sample are same, in other words, the means of the two sample are different, the average abnormal return of the two portfolios are different.

5. Conclusion

In my empirical tests, firms in the lowest OP/OS ratio outperform the highest one by average 0.22% per day. This fact shows that there is negative relation between OP/OS ratio and abnormal return. The possible reason is short selling constraints being the main driver for option trading. In other words, option trading can potentially quantify the degree of short sale constraints. To clarify, more option trading means the short sale costs are high. Options are used to bypass short-selling constraints, and this suggests that informed traders expect a reduction in prices, which should be reflected in lower returns. Based on the regression result, I conclude that there is a negative relationship between the OP/OS ratio and the abnormal return.

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Figure 1

Yearly option volume summary

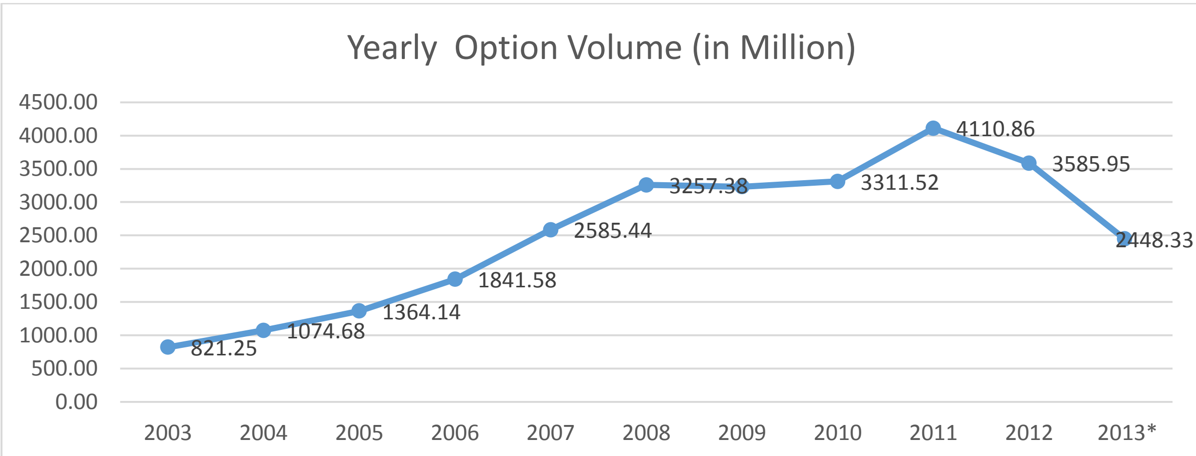

Figure 1 shows the option volume trend from 2003 to 2013.

* 2013 only include part of option data, which is from January 1st to August 31

Figure 2

Trend of OP/OS ratio from 2003 to 2013

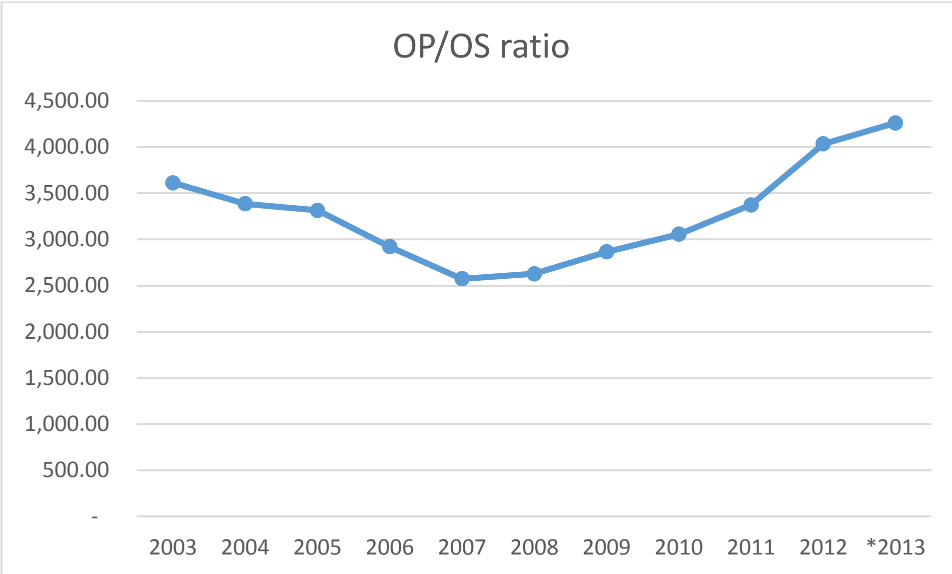

Figure 2 shows the trend of OP/OS ratio over year 2003 to 2013.

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Table 1

Option sample characteristics by year

Year	Firms	Firm-days	Mean	Std.Dev	Min	Max
2003	2438	432968	1896.79	12587.87	1	1316391
2004	2597	488282	2200.93	14187.35	1	1129264
2005	2802	529580	2575.88	17696.55	1	3285295
2006	3097	582279	3162.71	23344.99	1	4171612
2007	3449	649201	3982.49	32567.76	1	4529538
2008	3533	658166	4949.18	42833.25	1	5722888
2009	3444	634834	5091.48	46727.43	1	9729577
2010	3551	674352	4910.67	49001.17	1	8414093
2011	3846	694055	5922.96	70535.63	1	9203381
2012	3945	649938	5517.37	60803.8	1	7862492
2013*	4057	466883	5243.99	56920.62	1	8077156
ALL	3342	587322	4132.22	44739.13	1	9729577
Total		6460538				

Table1 provides the option sample characteristics from 2003 to 2013. For 2013, only data from January 1st to August 31 is included because the most recent data in Option Metrics is August 31,2013. The “Firms” column shows the number of firms in each year. The “Mean” column is the annual average option trading volume in unit per firm-day. The “Min” and “Max” column show the minimum and maximum number of one day option trading volume in unit. The second last row, which named “All”, shows the information of the option sample as a whole, 3342 is the annual average number of firm, 4,132.22 is the annual average number of option trading volume in unit. The last column shows the total number of firm-days in option sample.

Table 2

OP/OS ratio summary by year

OP/OS ratio yearly summary				
Year	Mean	Std.Dev.	Min	Max
2003	3,611.61	14,409.87	0.15127	917,127
2004	3,384.64	16,300.42	0.01945	3,902,677
2005	3,313.41	16,077.28	0.03685	2,739,939
2006	2,919.93	14,490.28	0.04097	2,214,841
2007	2,574.27	13,318.50	0.00649	2,184,051
2008	2,627.80	13,110.71	0.02930	1,818,488
2009	2,864.66	14,211.93	0.00845	1,815,281
2010	3,055.80	14,270.90	0.01095	1,714,728
2011	3,372.92	16,376.88	0.00935	2,217,374
2012	4,033.59	19,580.96	0.03275	3,322,086
*2013	4,261.09	24,706.33	0.00798	3,322,086
All	3,274.52	16189.36	0.00649	3,902,677

Table 2 shows the annual mean of OP/OS ratio across firms from year 2003 to 2013.The last row summarize the OP/OS ratio for the entire sample. * 2013 only include part of option data, which is from January 1st to August 31

Table 3

OP/OS ratio characteristic of 10 portfolios

Portfolio	Mean	Std.Dev	Min	Max
1(low)	12.30282	8.6464	0.0064929	45.80101
2	43.27556	15.72491	19.60227	103.6734
3	90.95605	26.47172	49.34313	190.23
4	166.1559	43.29514	95.34087	323.7871
5	289.009	71.70011	166.6709	535.5695
6	499.3116	122.81	283.8749	894.6
7	883.6048	233.3985	487.364	1554.431
8	1674.374	455.6901	879.5738	3074.106
9	3747.151	1243.85	1757.061	8204
10(high)	25015.71	45612.95	4537.8	3902677

Table 3 shows the statistical characteristic OP/OS ratio of each portfolio.

Table 4

Market capitalization characteristics of 10 portfolios

Portfolio	Firm-days	mean
1	639014	7657.1589
2	639012	9927.5216
3	639010	12271.3416
4	639012	11816.0293
5	639012	9270.3637
6	639009	6648.2969
7	639017	4948.1748
8	638908	4026.0808
9	639024	3605.372
10	638990	3929.0596
ALL	639001	7409.9399
Total	6390008*	

Table 4 provides the market capitalization characteristics of 10 portfolios for year 2003 to year 2013. The entire sample is divided into 10 portfolios based on OP/OS ratio. Portfolio one has the lowest ratio and portfolio ten has the highest ratio. The first column shows the number of the portfolio. The numbers in "mean" column are in millions. The second last row shows information for the entire sample. In average, there are 639001 firm-days observations in each portfolio and the average market capitalization for each portfolio is 7409.9399 million. The last row shows the total number of firm-days for the entire sample data. * 6390008 is different from the number (6460538) shows in table 1 because the entire sample data is slightly different from table 1 and table 4. The sample data of table 1 is the raw option sample downloaded from Option Metrics, the sample data of table 4 is obtained by merging the raw option sample with stock sample and then deleted the data which show negative number in market capitalization and missing value in OP/OS ratio and holding period return.

Table 5

The relation between Market Cap and OP/OS ratio

Panel A

The relation between market cap and OP/OS ratio								
	Market Cap				OP/OS ratio			
Market Cap	mean	Std.Dev	Min	Max	mean	Std.Dev.	Min	Max
Low	620.1596	408.8176	0.1308	1523.168	2794.581	9376.408	.0064929	2053961
High	12770.28	27927.85	1523.169	658152.8	3678.077	20892.16	.0243797	3902677

Panel A is obtained by dividing the entire sample data into two portfolios based on market capitalization. It shows the OP/OS ratio for low and high market capitalization portfolios. All numbers in Market Cap section are in million.

Panel B

T-test result (95% confidence interval)

Group	Obs	Mean
1	3195004	2794.581
2	3195004	3678.077
combined	6390008	3236.329
diff		-883.596
P-value		0.0000

Panel B shows the result of two sample T-test. It tests the mean of OP/OS ratio of the two portfolios. The null hypothesis of the T-test is the means of the two sample are same. The confident interval of this test is 95%. P-value of the test is 0.0000, which indicates rejecting the null hypothesis. From the result of the T-test, we can see the means of OP/OS ratio for these two portfolios are different.

Table 6

Summary of OP/OS ratio by major industry

SIC ID	Industry(major group)	Obs	Mean	Std.Dev	Min	Max
10-14	Mining	461304	1866.10	10620.70	0.0244	976433
15-17	Construction	71811	1874.89	9123.99	0.4323	624077
52-59	Retail Trade	347661	2036.63	9584.34	0.1066	899090
20-39	Manufacturing	2171025	2733.47	14236.51	0.0366	2739939
70-89	Services	873751	3081.23	13315.07	0.0410	3902677
50-51	Wholesale Trade	155199	3255.69	10730.81	0.2591	427810
99	Nonclassifiable	73437	3303.23	10686.15	0.1431	239366
91-97	Public Administration	1048	3715.93	6893.30	2.6588	39324
01-09	Agriculture, Forestry and Fishing	13000	3754.10	14452.75	0.2703	390164
60-67	Finance, Insurance and Real Estate	1199049	4106.27	21010.59	0.0065	3322086
40-49	Transportation, Communications, Electric, Gas and Sanitary service	600924	5185.61	23852.00	0.1016	2217374

Table 6 shows the summary of OP/OS ratio of different industries from Jan 1st 2003 to August 31st 2013. The first 2 digit of SIC is used to identify the major industry. The “Obs” column shows the total number of observations in each industry. The SIC ID that start with 99 are nonclassifiable. The table is organized by mean ascending order.

Table 7

Factor regression results of 10 portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	y	y	y	y	y	y	y	y	y	y
mktrf	1.090***	1.158***	1.119***	1.089***	1.059***	1.034***	1.017***	0.989***	0.960***	0.930***
	(0.00536)	(0.00363)	(0.00328)	(0.00295)	(0.00281)	(0.00273)	(0.00277)	(0.00262)	(0.00259)	(0.00250)
smb	0.535***	0.514***	0.496***	0.500***	0.536***	0.558***	0.559***	0.561***	0.591***	0.523***
	(0.0111)	(0.00755)	(0.00677)	(0.00607)	(0.00576)	(0.00561)	(0.00566)	(0.00536)	(0.00528)	(0.00506)
hml	-0.0117	0.0828***	0.0662***	0.0729***	0.0853***	0.0937***	0.0995***	0.139***	0.160***	0.167***
	(0.0126)	(0.00869)	(0.00782)	(0.00703)	(0.00668)	(0.00650)	(0.00655)	(0.00620)	(0.00611)	(0.00585)
umd	-0.0728***	-0.0739***	-0.0776***	-0.0748***	-0.0899***	-0.0926***	-0.103***	-0.100***	-0.119***	-0.121***
	(0.00699)	(0.00482)	(0.00436)	(0.00394)	(0.00374)	(0.00364)	(0.00368)	(0.00348)	(0.00342)	(0.00328)
Constant	0.00174***	0.00109***	0.000715***	0.000486***	0.000296***	0.000141***	-0.00008***	-0.00024***	-0.00031***	-0.00045***
	(0.000060)	(-0.000041)	(-0.000037)	(-0.000033)	(-0.000031)	(-0.000030)	(-0.000031)	(-0.000029)	(-0.000028)	(-0.000027)
Obs.	639,014	639,012	639,010	639,012	639,012	639,009	639,017	638,908	639,024	638,990
R-squared	0.084	0.184	0.206	0.235	0.246	0.252	0.243	0.256	0.258	0.259

The following tables present Fama-French four factors model across ten portfolios from year 2003 to year 2013. For 2013, only data from January 1st to August 31is included. The variable y shown in the second row is defined as Rpt-Rf, which is the daily holding period return minus the risk-free return rate. The regression use y as dependable variable and mktrf,smb,hml and umb as independent variables. The first row is the number of portfolios, portfolio one has the lowest OP/OS ratio and portfolio ten has the highest OP/OS ratio. The numbers with brackets are p-values. This table also presents the number of observations in each portfolio and the R- squared.

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8

The average OP/OS ratio and abnormal return of 10 portfolios

Portfolio	Alpha	OP/OS ratio
1(low)	0.00174	12.30282
2	0.00109	43.27556
3	0.000715	90.95605
4	0.000486	166.1559
5	0.000296	289.009
6	0.000141	499.3116
7	-0.0000802	883.6048
8	-0.0002377	1674.374
9	-0.0003074	3747.151
10(high)	-0.0004514	25015.71
1-10	0.0021914	-25003.4072
(1+2)-(9+10)	0.0035888	-28707.2826

Table 7 shows the alpha (abnormal return) and average OP/OS ratio of each portfolio. The second last row shows the difference in alpha and OP/OS ratio between portfolio one and ten, and the last row shows the difference in alpha and OP/OS ratio between the portfolio one and two and the portfolio nine and ten.

Table 9

T-test results for abnormal return (95% confidence interval)

Panel A: T-test result between portfolio 1 and portfolio 10

Group	Obs.	Mean
1	128	0.0018411
10	128	-0.0003875
combined	256	0.0007268
diff		0.0022285
p-value		0.0000

Panel B: T-test result between portfolio 2 and portfolio 9

Group	Obs.	Mean
2	128	0.0010826
9	128	-0.0002882
combined	256	0.0003972
diff		0.0013708
p-value		0.0000

This table shows the two sample T-test results of monthly abnormal return. From January 2003 to August 2013 there are 128 months, so the "Obs." column shows 128 observations. The first T-test tests the mean of abnormal return between portfolio one and ten. The second T-test tests the mean of abnormal return between portfolio two and nine. The p-value of both tests are zero, which indicates that the mean of the tested sample are different.

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