Empirical Study on Greed

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January 2016

Abstract

This paper studies cross-sectional stock returns from intrinsic and extrinsic point of view. We extend the model from Yin (Dec. 2015) to moving averages and we show a series of trading strategy that could explain some of the anomalies in the market. Intrinsically, investors can study Enterprise Value to interpret cross-sectional stock returns. Extrinsically, traders can generate alphas with great significances by trading off moving averages. We interpret the underlying emotions, greed and hope, in the market by looking at empirical results intrinsically and extrinsically.

1 Introduction

To explain the underlying emotions, greed and hope, in the market, we present two paths to analyze these psychological feelings. By looking at cross-sectional data, we can interpret empirical results from intrinsic and extrinsic point of view. Securities sold on the market bare certain amount of value. It is the value of how much each security worth by itself, hence it is the intrinsic value. Early literatures by Benjamin Graham discussed a lot of the fundamental indicators that we could be studying to understand intrinsic value. On the other side, market in which the securities are sold is on an auction bases. That is, traders buy and sell freely by bid and ask. This is largely due to negotiation and communication aspects between market participants. To date, we do not have any literature proving that this is completely rational. However, this does not hinder us to draw some reasonable arguments from applying the moving averages.

Based on Modigliani and Miller Theory, Yin (Nov. 2015) has examined the Market Value Balance Sheet (MVBS) from an accounting standpoint. The work, derived from MM Theory, describe a corporation from sum of Cash and Enterprise Value (EV) on the left side and sum of Debt (D) and Market Equity (ME) on the right side. The goal is to describe corporate activities with Enterprise Value (EV). Yin (Nov. 2015) pointed out that the scholars in behavioral finance and asset pricing barely used the model. Traditional cross-sectional study done by De Bondt and Thaler (1985) put a lot of attention on Long Run Reversals and in particular updating Fama-French three-factor model. Their work sort of stock universe by winners and losers which is a measurement of stock returns. They are able to construct a replica portfolio and generate a market-like return by a long portfolio in long-run losers and a short portfolio in long-run winners. However, this sort solely depends on market returns and does not take any other fundamental factors into consideration. Hawanini and Keim (1995) attempted to sort the stock pool by the size. They claim that small stocks have outperformed large stocks by about 12% a year over 1951-1989 time period. This argument has been developed on stock-picking skills between buying a lot of small stocks or big stocks. The answer goes back to study the risk-return in the stock profiles. Their paper also studied the stock universe by market-to-book sort, yet book value does a poor job of describing corporate activities. Fama and French (1993) also put a lot of effort in studying risk of book-to-market ratio. On the market value side, Jegadeesh (1990) examined the cross-sectional returns by the returns of small-, medium-, and large size-quintile portfolios in time t. However, these studies do not to describe how corporate activities over time affect cross-sectional stock returns.

First, this paper takes MM Theory and examine Enterprise Value by applying cross-sectional study on *compustat* stocks universe. We provide three methods to sort the stock universe. Among them, $\gamma_{i,t}$ is the most important one and it describes the change of Enterprise Value (EV) over Market Equity. The results are consistent with Piotroski (2000). We conclude an investor can construct a “greed” strategy such that he can generate alpha by buying the most “greedy” stocks and selling the least “greedy” stocks.

Next, we present a model looking at different time period persistence and momentum among cross-sectional returns. There are some literatures related to this topic. Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), and Wermers (1996) find evidence of persistence in mutual fund performance over short-term horizons of one to three years. Brinblatt and Titman (1992), Elton, Gruber, Das, and Hlavka (1993), and Elton, Gruber, Das, and Blake (1996) study mutual fund return predictability over longer horizons of five to ten years, and attribute this to manager stock picking skills. Jen (1969), however, presents contrary evidence and explains that good subsequent performance follows good past performance. Carhart (1992) explains that it is persistence in expense ratios that drive a lot of the long-term persistence in mutual fund performance. We are using moving averages, both Simple Moving Average $SMA(i,t)_n$ and Exponential Moving Average $EMA(i,t)_n$, to measure the stock returns.

2 Mathematical Model

2.1 Enterprise Value

From Market Value Balance Sheet (MVBS) model, we look at corporate activities (mergers and acquisitions, etc.) from market value of assets and market value of liabilities. The left side of the balance sheet is composed of Cash and Enterprise Value (EV) while the right side of the balance sheet is composed of Debt and Market Value of Equity, which has the following form:

$$MVA = MVL, \tag{1}$$

where the model denotes market value of assets on the left to be equivalent as market value of liabilities on the right. In detail, each component summarizes the following:

$$\begin{cases} D+E=MVL \\ C+EV=MVA \end{cases}. \tag{2}$$

We can take equation (1) and subtract Cash from both sides. Then we have the following equation:

$$EV = D + E - C \tag{3}$$

For the definition of Enterprise Value (EV), Yin (Nov. 2015) assumed that market value of debt (MVD) was Total Liabilities and used the book definition for consistency purpose: $EV = Total\ Liabilities + Total\ Shareholders'\ Equity - Cash$. This definition is consistent in which each of the component comes from accounting measures. For each asset i, Yin (Nov. 2015) sort the stock universe by 1) percentile of how much Enterprise Value (EV) in Total Assets, and 2) change of Enterprise Value (EV) over Total Assets. Both definitions write the following form,

$$\omega_i = \frac{EV_i}{TA_i}, \tag{4}$$

and

$$\phi_i = \frac{\triangle EV_i}{TA_i} = \frac{EV_i - lag(EV_i, 12)}{TA_i}. \tag{5}$$

However, this definition does not include anything about market value aspect of the corporations, which we found to be lack of persuasive power. Hence, we redefine Enterprise Value (EV) in this paper as the following,

$$EV = Total\ Liabilities + Market\ Equity - Cash. \tag{6}$$

In this paper, we use this definition for Enterprise Value and we look at corporation activities from sum of Total Liabilities and Market Equity subtracted Cash of a certain firm. For for any asset i over t-period, we can rewrite equation (6) in the following form,

$$EV_{i,t} = TL_{i,t} + ME_{i,t} - C_{i,t}. \tag{7}$$

However, EV_i does not reflect anything about how certain changes may have happened for a company. By using function $lag(x,t)$, we calculate x shifts t period(s) into the past, $lag(x,t) = x_{t-1}$. We take 1st order of Enterprise Value (EV). We denote this as growth rate δ and the definition writes the following form,

$$\delta EV_{i,t} = \frac{EV_{i,t} - lag(EV_{i,t}, t)}{lag(EV_{i,t}, t)}, \tag{8}$$

and we also take the 2nd order of Enterprise Value (EV). We take the change of growth rate δEV for any asset i over t-period. The definition writes the following form,

$$\delta(\delta EV_{i,t})_{i,t} = \frac{(\delta EV_{i,t}) - lag((\delta EV_{i,t}), t)}{lag((\delta EV_{i,t}), t)}, \tag{9}$$

Fama and French (1993), De Bondt and Thayler (1985), and Jegadeesh (1990) all presented models implying the importance of book-to-market factor. To really show how changes of corporate activities and market equity affect cross-sectional stock returns, we have the following definition,

$$\gamma_{i,t} = \frac{\triangle EV_{i,t}}{ME_{i,t}} = \frac{EV_{i,t} - lag(EV_{i,t}, t)}{lag(ME_{i,t}, t)}, \tag{10}$$

2.2 Moving Averages

Moving Averages are used by chartist in practice. To date, there has not been any successful literatures document the advantage of trading with moving averages.

Moving Averages can be simple or exponentially. Simple Moving Average (SMA) records a smoother path than observed population where as Exponential Moving Average (EMA) puts more weight as time goes on on Simple Moving Average. For each observed price, we can calculate simple moving averages, as below

$$SMA(i,t)_n = \frac{1}{n}\sum_{j=1}^{n} P(i,t)_j, \tag{11}$$

so far each stock i at time t we can calculate $n-day$ simple moving averages by taking the sum of the n days observed prices and divided by n. We can apply this to data of cross-sectional returns. We first calculate take the first derivative of observable prices in the market in the following form. That is the return of stock price, $\delta P_{i,t}$, in the following form,

$$\delta P_{i,t} = \frac{\triangle P_{i,t}}{P_{i,t-1}} = \frac{P_{i,t} - lag(P_{i,t}, t)}{lag(P_{i,t}, t)}, \tag{12}$$

and then we apply simple moving averages to the return. We have,

$$SMA(\delta P_{i,t})_n = \frac{1}{n}\sum_{j=1}^{n} (\delta P_{i,t})_j, \tag{13}$$

and this allows us to capture a slower moving time-series of price actions. We can sort cross-sectional stock returns by $SMA(\delta P_{i,t})_n$, outperforming FF-3 replica.

Moreover, we can look at exponential moving averages (EMA). We define exponential moving average as a weighted moving averages by taking a weight distributed in perspective of time between observed data and simple moving averages of observed data. The concept of exponential comes from the fact that the formula is constructed such that the weight on the simple moving averages increases when the time lags longer into the past. There is no particular reason we have this definition. One can do the opposite and still achieve the same arguments. The formula grows the following form,

$$EMA(i,t)_n = P_{i,t}\theta_n + SMA(i,t)_n(1-\theta_n), \tag{14}$$

with $\theta_n = 1/(n+1)$ to be a weight calculated exponentially. Hence, equation (15) can also be extended to the following form,

$$EMA(i,t)_n = P_{i,t}\frac{1}{(n+1)} + \frac{1}{n}\sum_{j=1}^{n} P(i,t)_j(1 - \frac{1}{(n+1)}). \tag{15}$$

Next, we apply exponential moving averages to return of stock prices, $\delta P_{i,t}$, and we will have the following formula,

$$EMA(\delta P_{i,t})_n = (\delta P_{i,t})\frac{1}{(n+1)} + \frac{1}{n}\sum_{j=1}^{n}(\delta P_{i,t})_j(1 - \frac{1}{(n+1)}). \tag{16}$$

2.3 Sort and compare to FF-3 replica

Next, we apply Fama-French 3-factor model to test this idea. We apply the three definitions above to sort the *compustat* stock universe. We divide the stock universe into five quintiles and sort by each of the definition above with different time periods. Then we examine the return by market factor, size, and book-to-market.

The FF-3 in our test has the following form:

$$r_{i,t} = \beta^i_{MKT}MKT_t + \beta^i_{SMB}SMB_t + \beta^i_{HML}HML_t + \epsilon_{i,t}, \tag{17}$$

3 Data

We take the *compustat* data from Wharton Research Data Services and we had the stock universe from 1950 to 2013 monthly data. We convert the data to month-by-firm matrices and apply matrix operations for the noted definition of each factor.

4 Results

4.1 Summary

We conduct cross-section study to examine Enterprise Value (EV) and the change of Enterprise Value (EV) based on Yin (Nov. 2015). First, we sort the stock universe by the growth rate $\delta EV_{i,t}$ by equation 8. Then we sort the universe by $\gamma_{i,t}$ based on equation 10. Last we sort the universe by $\delta(\delta EV_{i,t})$ by equation 9. We conduct cross-section regression to study the concept Enterprise Value (EV) in the MVBS model. Yin (Nov. 2015) used both equal-weight and value-weight. This paper we drop equal-weight because it is too far away from the practice and this method does not present results close to the industry numbers. All portfolios are under value-weight for each sort. We conducted all studies with FF-3 and we drop Carhart 4-factor model which was originally applied in Yin (Nov. 2015).

Yin (Nov. 2015) have shown that all sorts present excess return of large portfolio than small portfolio to be a positive percentile. In other words, an investor could construct a portfolio simply by a long portfolio of high Enterprise Value (EV) stocks (or big increase on Enterprise Value) and a short portfolio of low Enterprise Value (EV) stocks (or small increase on Enterprise Value) blindly with NYSE breaks and he could make an average of 0.502% (from "XRet" in Table (1)). This results of a universally positive excess return from the large Enterprise Value (EV) portfolio minus the small Enterprise Value (EV) portfolio show consistency with traditional FF-3 sorted by market cap, implying the same trading strategy and investment philosophy between an investor using book-to-market and an investor using Enterprise Value (EV). As Table (1) shown, a strategy by FF-3 can be replicated with -0.057, -0.137, and 0.529 loadings on market, size, and book-to-market factors. The extremely significant positive loading on book-to-market ratio shows that this is a value strategy. The investment decisions betting on expected increase on corporate activities is consistent with value investing in the efficient market. We find further consistent results as Yin (Nov. 2015).

Next, we conduct cross-section study to examine how different sorts among definitions derived from moving averages affect alphas throughout different time period. We have four panels presented in Table (4). We arbitrarily choose time period to be 10-, 20-, 30-, 40-, and 50-month to run time-series regressions. We put everything together to form panel depending on the sort. There are 14 out of 20 t-stat in the table that are greater than 1.96, which are statistically significant.

Last, we conclude the trading strategies from all of the examinations.

4.2 Sort by $\delta EV_{i,t}$

This sub-section we sort the universe by $\delta EV_{i,t}$. For each asset i, we calculate the change of $EV_{i,t}$ based on different time t-period. We select 1-, 2-, 3-, 4-, and 5- year in the past. For t-period, we sort stock universe by $\delta EV_{i,t}$ to ten deciles and we examine each portfolio with FF-3 model. In Table (3) Panel A, we present the access return of each L/S strategy for each t-period in every sort.

We observe that access return increases as time lags longer into the past. For each sort, access return is calculated from the difference of the winning portfolio and the losing portfolio for each of the t-period. For example, we sort the universe by by the growth rate $\delta EV_{i,12}$ into ten deciles and we take the difference of top decile and bottom decile, 0.172% monthly return with t-stat to be 1.06. This strategy beats FF-3 benchmark by 0.394% with t-stat at 2.48. The significant t-stat on alpha shows us that an investor can simply buy the companies with large growth rate $\delta EV_{i,12}$ in the past year and sell the companies with small growth rate $\delta EV_{i,12}$ in the same period to beat the market.

This strategy turns out to be the same as large-cap growth stocks strategy. Table (4) shows us a significant negative loading on HML factor for this strategy. There is a 0.511 loading tilted to growth stocks more than value stocks with a t-stat of 8.47. For each of the period 12-, 24-, 36-, 48-, and 60-month, we have loadings on book-to-market ratio to be -0.511, 0.673, 0.696, 0.810, and 0.844 with corresponding t-stat to be -8.47, 11.63, 12.78, 16.75, and 18.21. We see monotonicity between t-period and loadings on book-to-market ratio as well as corresponding t-stat. This is consistent with our expectation since equation 7 tells us that an increase on $ME_{i,t}$ will result in an increase of $EV_{i,t}$ as well. This means the longer in the past we study Enterprise Value (EV) changes the more weight we would be putting on value stocks.

4.3 Sort by $\gamma_{i,t}$

This sub-section we sort the universe by $\gamma_{i,t}$, which is the percentage of the increase on Enterprise Value (EV) for an asset i during t-period over the $ME_{i,t}$ of that asset during the same period. This modification is to mimic the book-to-market ratio. For high book-to-market ratio stocks, we call this tilt or a positive loading on B/M factor a value strategy. If an investor is targeting the stocks that have significant growth of Enterprise Value (EV), the investor is really trying to invest in the value of the company, which is high book-to-market ratio stocks. On one hand, EV is calculated from discounting the net cash flow of the company. On the other hand, EV is also increasing if there is a significant buyer in the market trying to push the price up, hence increasing market value of equity $ME_{i,t}$. This type of sort is really trying to discovering EV changes corresponding to market value of equity.

From Table (3) Panel B, we present, in each row, the L/S strategy on $\gamma_{i,t}$ sort during different t-period. The apparent results show us a monotonicity between t-period and t-stat of alpha. The The alpha of each sort for each t-period increases as the time t-period lags longer into the past. We present 12-, 24-, 36-, 48-, and 60-period lagged into the past. That is to say for each of these periods, we have increasing t-stat on access return and t-stat on alpha. This shows us that as times lags longer into the past an investor will be making higher expected return on the portfolios and the results are more and more likely to happen.

This part we also find consistent results as we sort by $\delta EV_{i,t}$ presented in Section 4.2. That is to say, an investor is investing in value stocks when he targets long-term Enterprise Value (EV) growth. This is true disregard if he is comparing the growth to Enterprise Value or Market Equity.

4.4 Sort by $\delta(\delta EV_{i,t})$

We sort the universe by $\delta(\delta EV_{i,t})$. In Table (3) Panel C, we do not observe any monotonicity between any two parameters. The t-stat are relatively random compare to those in other panels. The highest t-stat is 1.78 for $\delta(\delta EV_{i,12})$ and this gives an alpha of 0.107 with insignificant t-stat at 1.23. We conclude that this model failed to show us any regular changes over time on the second order of Enterprise Value (EV).

Although not apparent, the value strategy does appear in Table (4) Panel C as we expected. Panel C shows us relatively increasing loadings from -0.118 to 0.211 with significant t-stat on HML factor. The recent, 12-month, sort would put more weight growth stocks. As time lags longer into the past, the loadings turn positive and gradually increasing. This is consistent with all the findings above in Section 4.2 and Section 4.3.

4.5 Sort by $SMA(\delta P_{i,t})_n$

We sort the stock universe by simple moving averages in Panel D, Table (4). The results are universally the same disregard the time-period in the model. The excess return has a t-statistic at 1.72 and the α has a t-statistic of 1.08. Although the results not statistically significant, they tell us that for Simple Moving Average trading strategy is not dependent on the difference of time frame. This result does not surprise us since Simple Moving Average is generated directly from cross-sectional stock returns.

4.6 Sort by $EMA(\delta P_{i,t})_n$

We sort the stock universe by exponential moving averages in Panel E, Table (4). The sort by EMA gives us a relatively monotonic excess monthly returns, ranging from 0.344% to 0.528%. The t-statistics for all of the excess returns are above 1.96. Moreover, we achieved significantly positive alphas for all five time periods. For an investor who trade by 10-month period, he could mandatorily buy portfolios performed poorly in 10-month and sell portfolios performed well in 10-month and create an alpha of 0.461% monthly excess returns than FF-3.

Based on the construction of EMA, we know that the definition would put more weight on SMA as time lags longer into the past. That is, an investor could change different time period to achieve similar strategy as short-run reversal and long-run reversal. In Panel E, we observe that 40-month period is relatively insignificant compared to the other periods. The second significant period is 50-month. This is equivalent to the mechanism as if an investor is running long-run reversal strategy.

4.7 Sort by $\delta P_{i,t} - SMA(\delta P_{i,t})_n$

We sort the stock universe by difference between stock returns and SMA in Panel F, Table (4). That is, we are looking at how much bigger the return of stock universe is compared to simple moving averages for each period. By taking different arbitrary number of time periods into consideration, we are looking at a trading strategy targeting how far away the price is deviating from moving averages.

We can use Graph (1) as an assistance for us. Graph (1) is projected as the price and simple moving averages on prices. This is a time-series plot before taking derivatives. Our model is constructed by looking at the derivatives of these plots. For each line (plot), there will be an imagined tangent as time changes, which is the first order derivative.

In other words, we are looking at how fast the price grows higher than simple moving averages. For each time period t, the model is simulating an investor mandatorily holding a portfolio with a long position in stocks that have similar returns in price and SMA and a short position in stocks that have big difference in price and SMA. Intuitively, this is almost similar as balance your portfolio when it is close to moving averages or is crossing over moving averages and sell when it is far away from moving averages.

4.8 Sort by $\delta P_{i,t} - EMA(\delta P_{i,t})_n$

We sort the stock universe by difference between stock returns and EMA in Panel G, Table (4). This strategy is mechanically similar as sorting by $\delta P_{i,t} - SMA(\delta P_{i,t})_n$, yet there is a big difference between moving averages. By equation (11), (14), and (15), the EMA puts more weight on SMA than return of price as time period lags longer into the past. That is, we expect EMA to look more like SMA when time lags longer but to look more like return of price when time lags shorter. This characteristics detailed by the definition (11), (14), and (15) present to us a slightly better situation.

The data presented in Table (4) show us all the t-statistics for different periods to be the same between sorting by $\delta P_{i,t} - SMA(\delta P_{i,t})_n$ and sorting by $\delta P_{i,t} - EMA(\delta P_{i,t})_n$ except for t to be 40-month. However, we observe that t-statistic for 40-month in Panel G is 2.58 which is bigger than that of Panel F at 2.57. The little detail show us that if we expand the time period and lag the period longer in the past we would have achieved a more significant results.

The results from cross-sectional stock returns showed us we can generate an alpha of 0.42% monthly by trading of exponential moving averages with 10-month period, which is consistent with the result of short-run reversal.

4.9 Comparison of All L/S Strategies

We summarize all L/S portfolios with coefficients on market, size, and book-to-market factors in Table (4). Among three panels, A, B, and C, are the results for coefficients and corresponding t-stat for all FF-3 model replicas on $\delta EV_{i,t}$, $\gamma_{i,t}$, and $\delta(\delta EV_{i,t})$ sorts. Yin (Nov. 2015) have conducted parallel study on ω_i, and ϕ_i both lagged 12-month in the past. In the previous work by Yin (Nov. 2015), the results from his test suggested the highest Sharpe Ratio that can be constructed is the portfolio sort by the change of Enterprise value (EV) over Total Assets. Moreover, the more decile the universe is separated the more attractive the Sharpe Ratio is. His L/S replica portfolio of five breaks gives a Sharpe Ratio of 0.4299 and the L/S replica portfolio of ten breaks gives a Sharpe Ratio of 0.5511, compared to the Sharpe Ratio of the replica portfolio with traditional sort by market value to be 0.3066. Although his work generated a higher Sharpe Ratio by change of Enterprise Value (EV) over Total Assets, he argued that the Change of Enterprise Value (EV) is the key here in this model. When a company acquires an asset, it is the value added to the whole company from that acquisition that attracts and affects decision making process.

The work is doing doing a fine job describing how previous year Enterprise Value (EV) affecting cross-sectional stock returns at present time. However, such model provides no explanatory power for long time into the past, hence it does a poor job in forecasting ability especially further into the future. Table (2) presents the table from Yin (Nov. 2015) and we can argue selected winning strategy from Table (1) with 0.5511 Sharpe Ratio is actually a lucky event.

Table (3) we present three panels on top the foundation of Yin (Nov. 2015) and we show that investment strategy with studying the change of Enterprise Value (EV) actually gradually improves as time goes along. This pattern is extremely obvious in Panel B of Table (3) and similar patterns can be observed for other panels. To study cross-sectional stock returns, Enterprise Value (EV) and the change of Enterprise Value (EV) are two essential factors before sound investment decisions can be made.

Every time there is a merger or acquisition happen, the Enterprise Value (EV) changes. The corporate activities could be generating synergies and could also destroying synergies. By studying the change of Enterprise Value (EV), we are really trying to capture whether the corporation is aggressive or not in its expansions. If a management team or a board is participating in M&A deals one by one, it is representative that this is a very greedy and aggressive group of people managing this company. The truth behind the act of M&A deals simply states that there is underlying greed in this security. If a person does not want to grow his money, why on earth would he buy new assets and take on more risk? Hence, we are really measuring "hope" or "greed" in the underlying assets. By calculating $\delta EV_{i,t}$, $\gamma_{i,t}$, and $\delta(\delta EV_{i,t})$, we can construct portfolios that buy the companies people hope the most and sell the companies people hope the least, outperforming the market with an positive alpha. Moreover, an investor can further its certainty and achieve the results with a portfolio constructed studying longer time lagged into the past.

Table (4) present the reader four panels from technical perspective of cross-sectional stock returns. This aspect describes a series of scenarios other than Enterprise Value (EV). The prior is an extrinsic point of view and the latter an intrinsic point of view. Overall, we do observe some significant alpha in Exponential Moving Average and the difference between cross-sectional stock price and the two moving averages, $SMA(\delta P_{i,t})$ and $EMA(\delta P_{i,t})$ respectively. Panel E in Table (4) sort stock universe directly based on the Exponential Moving Average of the first order of cross-sectional stock returns. We observe significant alpha in 10-month and 50-month period, which is consistent with short- and long-run reversal strategies. Moveover, we observe relatively consistent alpha in Panel F and Panel G, which describes cross-sectional stock returns sort by $\delta P_{i,t} - SMA(\delta P_{i,t})_n$ and $\delta P_{i,t} - EMA(\delta P_{i,t})_n$. The alpha ranged from 2.57 to 2.92 consistent for these two panels and long/short strategies have shown Sharpe Ratios that are slightly above market.

5 Conclusion

This paper updates the previous work accomplished by Yin (Dec. 2015) with models expands into different time t-period. Based on previous work conducting a series of cross-sectional study on examining the Enterprise Value (EV) in the Market Value Balance Sheet (MVBS) model by Modigliani and Miller (1958), this paper answers the question of how the growth rate of Enterprise Value for a certain asset during t-period of time will affect cross-sectional stock returns. We further present technical terms, moving averages, to describe stock returns and we invent potential trading strategies based on the moving averages.

Yin (Dec. 2015) updates previous work by Yin (Nov. 2015) and creates new definition of growth rate on Enterprise Value (EV) $\delta EV_{i,t}$, change on Enterprise Value (EV) over Total Assets $\gamma_{i,t}$, and second order of Enterprise Value (EV) $\delta(\delta EV_{i,t})$. By sorting the *compustat* stock universe under these three categories above, we can further study a more accurate method about Enterprise Value (EV) on how its change over different time affects cross-sectional stock returns. The results, quite astonishingly, tells us that a strategy designed to invest in companies with increasing growth rate or high growth rate of Enterprise Value (EV) can outperform market with a positive alpha. Moreover, this alpha can be more significant if investors take longer t-period into consideration when studying the underlying asset.T the paper only explains the problem from a intrinsic point of view. However, such strategy provides only from corporate point of view. It is not a reflection of other traders or chartist on the street.

In this paper, we present Simple Moving Averages (SMA) and Exponential Moving Averages (EMA) to describe cross-section stock returns. By ignoring noisy prices, we are able to look at a smoother price action. Then we present results from cross-sectional studies and we invent potential trading strategies. Similar to short-run reversal and long-run reversal, investor can trade off moving averages and the difference between cross-sectional stock returns between the moving averages of cross-sectional stock returns. This paper explains the same set of data with an extrinsic point of view.

Among all, the sort that describes change on Enterprise Value (EV) over Total Assets $\gamma_{i,t}$ show most significant results and the forecasting ability improves as time lagged deeper into the past. On the other hand, the sort that looks at the difference between cross-sectional stock returns and the moving averages of cross-sectional stock returns show the most significant results in the panel. Hence, we can write an extension of FF-3 model in the following form, denoting each parameter as λ,

$$r_{i,t} = \beta^i_{MKT}\lambda_{MKT,t} + \beta^i_{SMB}\lambda_{SMB,t} + \beta^i_{HML}\lambda_{HML,t} + \beta_i\gamma_{i,t} + \epsilon_{i,t}, \tag{18}$$

or the following if to avoid multicollinearity,

$$r_{i,t} = \beta^i_{MKT}\lambda_{MKT,t} + \beta^i_{SMB}\lambda_{SMB,t} + \beta_i\gamma_{i,t} + \epsilon_{i,t}. \tag{19}$$

As a summary, we expect investors to outperform market if investors construct portfolios by buying the stocks with higher increase on Enterprise Value (EV) and selling stocks with lower increase or higher decrease on Enterprise Value (EV). We further expect such strategy provides results more accurately if time in the study is lagged longer into the past. We call this the "greed" (or "fear") factor. Although it is hard to argue one factor can describe an emotion in the market, we believe it is a start to measure a majority of human emotions in the underlying assets of a portfolio.

6 Reference

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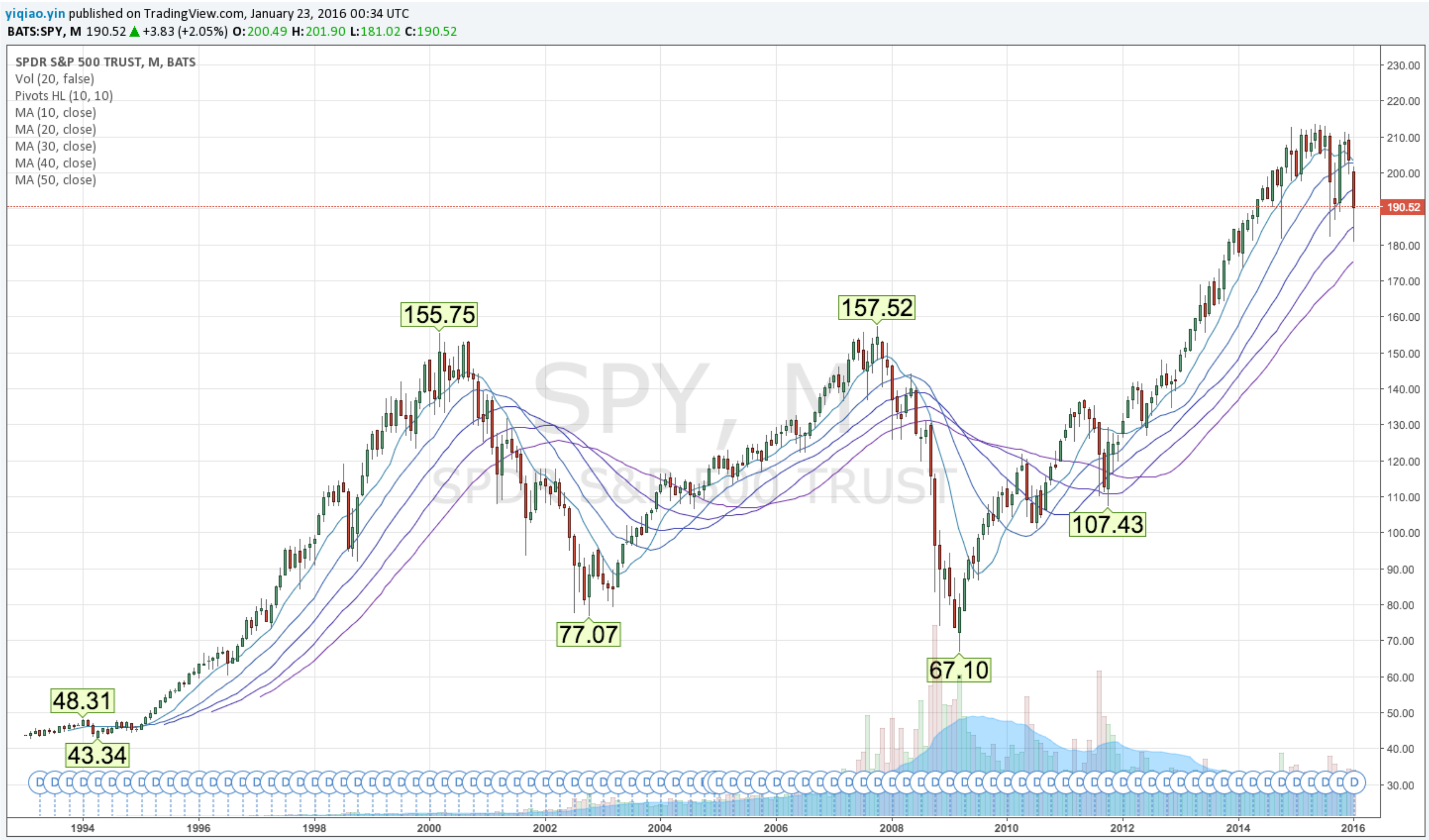
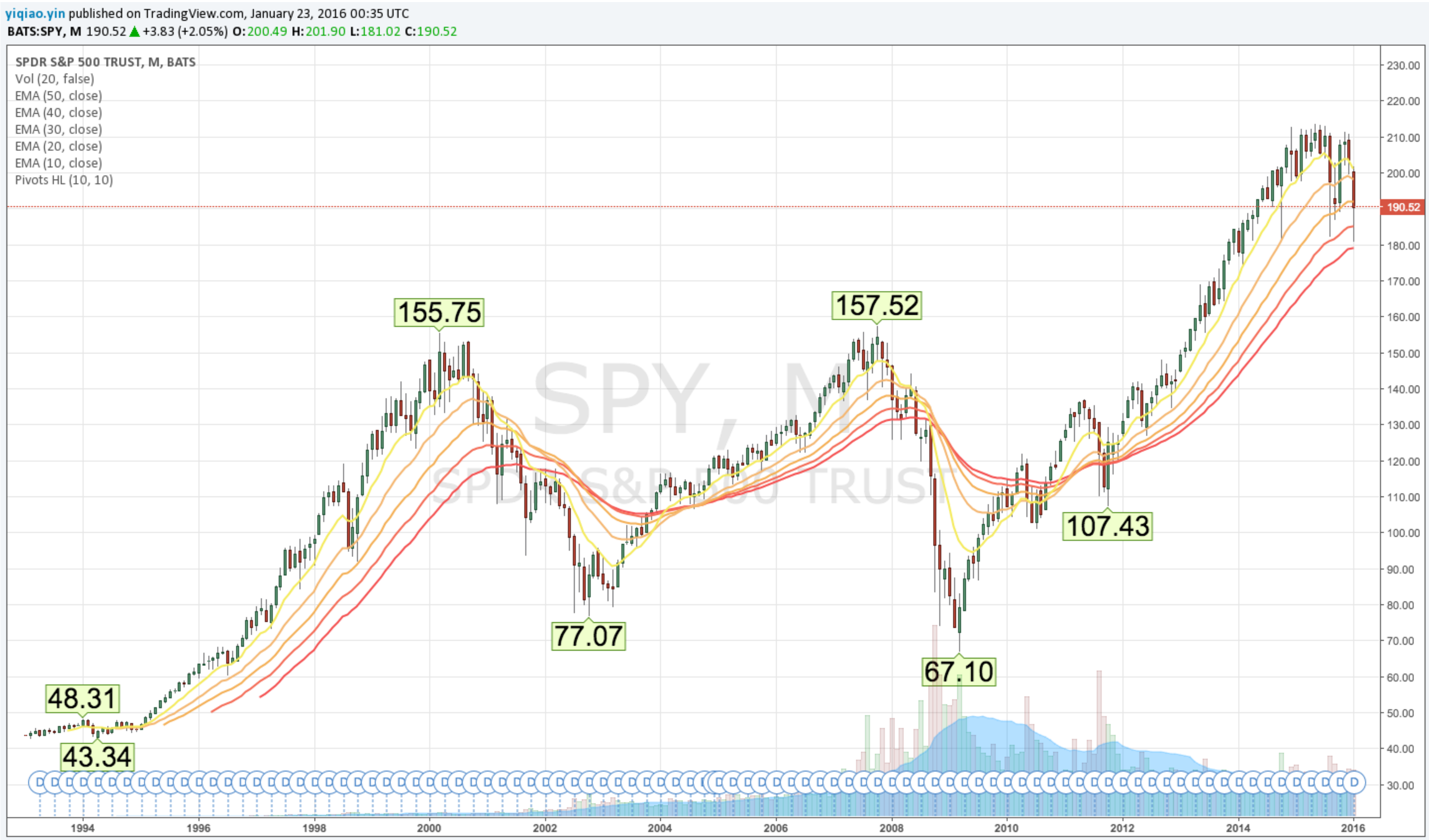
7 Graphs

Graph 1. This is monthly candlestick from Jan. 1st, 1993 to Jan. 1st, 2016. The graph also calculates SMA for the prices. It is a plot before taking derivatives. Chart is generated by tradingview.com.



Graph 2. This is monthly candlestick from Jan. 1st, 1993 to Jan. 1st, 2016. The graph also calculates EMA for the prices. It is a plot before taking derivatives. Chart is generated by tradingview.com.



8 Tables

Table 1. The table uses *compustat* universe from 1950 to 2014 monthly data as sample. The table is sorted by the percentile of how much Enterprise Value (EV) changed in the past 12 months over Total Assets, value weighted from small to large (1-10) portfolios by NYSE breaks on FF-3. The entries without brackets are coefficients and the entries with brackets are t-statistics. The figure presents the access returns of each portfolios.

	XRet	Alpha	MKT	SMB	HML
1	0.367	-0.233	1.138	0.160	-0.288
	[1.78]	[-3.34]	[67.43]	[6.50]	[-10.88]
2	0.644	0.071	1.082	0.200	-0.293
	[3.25]	[1.09]	[68.17]	[8.61]	[-11.78]
3	0.547	0.022	1.039	-0.053	-0.221
	[3.04]	[0.35]	[68.92]	[-2.43]	[-9.35]
4	0.561	0.039	0.949	-0.070	-0.070
	[3.51]	[0.69]	[69.28]	[-3.47]	[-3.27]
5	0.693	0.122	0.982	-0.129	0.049
	[4.32]	[2.14]	[71.08]	[-6.36]	[2.26]
6	0.683	0.160	0.916	-0.062	-0.014
	[4.48]	[2.93]	[69.50]	[-3.19]	[-0.68]
7	0.679	0.086	0.927	-0.105	0.194
	[4.47]	[1.40]	[62.85]	[-4.88]	[8.38]
8	0.616	0.007	0.938	-0.042	0.187
	[3.95]	[0.11]	[60.61]	[-1.86]	[7.69]
9	0.839	0.153	0.993	0.153	0.213
	[4.92]	[2.23]	[59.97]	[6.33]	[8.18]
10	0.869	0.095	1.081	0.297	0.241
	[4.49]	[1.15]	[54.04]	[10.17]	[7.67]
L/S	0.502	0.328	-0.057	0.137	0.529
	[4.36]	[3.13]	[-2.24]	[3.71]	[13.31]

Table 2. This is a summary table for all L/S strategy portfolio from Table (1) - (16), using the *compustat* universe from 1950 to 2014 monthly data as sample. The table is sorted by how much Enterprise Value (EV) in Total Assets, change on Enterprise Value (EV) over Total Assets, and Enterprise Value (EV) over Total Assets, value weighted from small to large (1-5, 1-10) portfolios by NYSE breaks on FF-3. The first row represents the excess returns, alpha, market premium, small-minus-big, and high-minus-low. The following rows are separated by the sorts accordingly. The entries without brackets are coefficients and the entries with brackets are t-statistics. SR_1 refers to the Sharpe Ratio for the series of portfolios equally weighted. SR_2 refers to the Sharpe Ratio for the series of portfolios value weighted.

	XRet	Alpha	MKT	SMB	HML	XRet	Alpha	MKT	SMB	HML	SR_1	SR_2
$\omega_i = EV_i/TA_i$												
	LS in quintiles					LS in deciles						
L/S	0.169	0.300	0.140	0.071	-0.654	0.103	0.289	0.135	0.164	-0.849	0.1865	0.0900
	[1.49]	[3.41]	[6.58]	[2.29]	[-19.54]	[0.72]	[2.65]	[5.13]	[4.24]	[-20.46]		
$\phi_i = \triangle EV_i/TA_i = EV_i - lag(EV_i, 12)/TA_i$												
	LS in quintiles					LS in deciles						
L/S	0.333	0.201	-0.082	0.011	0.516	0.502	0.328	-0.057	0.137	0.529	0.4299	0.5511
	[3.40]	[2.43]	[-4.12]	[0.37]	[16.45]	[4.36]	[3.13]	[-2.24]	[3.71]	[13.31]		
Replica of traditional FF-3 sort by market value												
	LS in quintiles					LS in deciles						
L/S	0.446	-0.164	0.064	0.373	1.225	0.461	-0.282	0.074	0.583	1.431	0.3066	0.2529
	[2.88]	[-3.10]	[6.09]	[21.76]	[80.78]	[2.38]	[-3.41]	[4.52]	[21.69]	[60.16]		

Table 3. This is a summary table of the alphas from each L/S strategy for all of the sorts of Enterprise Value (EV). Panel A is the sort of the first order of Enterprise Value (EV) during the past t-period. Panel B is the sort of the change of Enterprise Value over Market Equity (ME) during the past t-period. Panel C is the sort of the second order of Enterprise Value (EV) during the past t-period.

Panel A	XRet	t-stat	Alpha	t-stat	+/- L or S
Sort by $\delta EV_{i,t} = (EV_{i,t} - lag(EV_{i,t}, t))/lag(EV_{i,t}, t)$					
12-month	0.172	1.06	0.394	2.48	t-(t-1)
24-month	0.093	0.56	-0.169	-1.10	(t-1)-t
36-month	0.266	1.64	-0.001	-0.01	(t-1)-t
48-month	0.272	1.75	0.010	0.01	(t-1)-t
60-month	0.233	1.52	-1.040	-0.32	(t-1)-t
Panel B	XRet	t-stat	Alpha	t-stat	+/- L or S
Sort by $\triangle EV_{i,t}/ME_{i,t} = (EV_{i,t} - lag(EV_{i,t}, t))/ME_{i,t}$					
12-month	0.026	0.17	-0.169	-1.10	(t-1)-t
24-month	0.232	1.49	-0.004	-0.02	(t-1)-t
36-month	0.406	2.61	0.142	1.02	(t-1)-t
48-month	0.343	2.31	0.146	1.13	(t-1)-t
60-month	0.383	2.73	0.207	1.70	(t-1)-t
Panel C	XRet	t-stat	Alpha	t-stat	+/- L or S
Sort by $\delta(\delta EV_{i,t})_{i,t} = (\delta EV_{i,t} - lag(\delta EV_{i,t}, t))/lag(\delta EV_{i,t}, t)$					
12-month	0.155	1.78	0.107	1.23	(t-1)-t
24-month	0.107	1.14	0.065	0.70	(t-1)-t
36-month	0.073	0.78	-0.006	-0.06	(t-1)-t
48-month	0.129	1.42	0.037	0.40	(t-1)-t
60-month	0.102	0.93	-0.008	-0.07	(t-1)-t

Table 4. This is a summary table of the alphas from each L/S strategy for all of the sorts of moving averages. There are four panels in this table, D, E, F, and G. each panel is sorted by different different definition derived from moving averages. Panel D is sort by the SMA of cross-sectional stock returns. Panel E is sort by the EMA of cross-sectional stock returns . Panel F is sorted by the difference between cross-sectional stock returns and SMA. Lastly, Panel G is sorted by the difference between cross-sectional stock returns and EMA.

Panel D	XRet	t-stat	Alpha	t-stat	+/- L or S
Sort by $SMA(\delta P_{i,t})_n = \frac{1}{n}\sum_{j=1}^{n}(\delta P_{i,t})_j$,					
10-month	0.285	1.72	0.179	1.08	(t-1)-t
20-month	0.285	1.72	0.179	1.08	(t-1)-t
30-month	0.285	1.72	0.179	1.08	(t-1)-t
40-month	0.285	1.72	0.179	1.08	(t-1)-t
50-month	0.285	1.72	0.179	1.08	(t-1)-t
Panel E	XRet	t-stat	Alpha	t-stat	+/- L or S
Sort by $EMA(\delta P_{i,t})_n = (\delta P_{i,t})\frac{1}{(n+1)} + \frac{1}{n}\sum_{j=1}^{n}(\delta P_{i,t})_j(1 - \frac{1}{(n+1)})$					
10-month	0.528	3.62	0.461	3.15	(t-1)-t
20-month	0.495	3.39	0.419	2.88	(t-1)-t
30-month	0.497	3.41	0.424	2.91	(t-1)-t
40-month	0.344	2.37	0.253	1.75	(t-1)-t
50-month	0.514	3.53	0.448	3.08	(t-1)-t
Panel F	XRet	t-stat	Alpha	t-stat	+/- L or S
Sort by $\delta P_{i,t} - SMA(\delta P_{i,t})_n$					
10-month	0.484	3.36	0.420	2.92	(t-1)-t
20-month	0.473	3.28	0.398	2.77	(t-1)-t
30-month	0.475	3.29	0.399	2.77	(t-1)-t
40-month	0.179	1.30	0.346	2.57	(t-1)-t
50-month	0.483	3.36	0.411	2.86	(t-1)-t
Panel G	XRet	t-stat	Alpha	t-stat	+/- L or S
Sort by $\delta P_{i,t} - EMA(\delta P_{i,t})_n$					
10-month	0.484	3.36	0.420	2.92	(t-1)-t
20-month	0.473	3.28	0.398	2.77	(t-1)-t
30-month	0.475	3.29	0399	2.77	(t-1)-t
40-month	0.180	1.31	0.347	2.58	(t-1)-t
50-month	0.483	3.36	0.411	2.86	(t-1)-t

Table 5. This is a continued table from Table 3. The table summarizes of all the FF-3 factor coefficients for L/S replicas and corresponding t-statistics for all three panels. Panel A is the sort of the change of Enterprise Value (EV) over Enterprise Value (EV) during the past t-period. Panel B is the sort of the change of Enterprise Value over Market Equity (ME) during the past t-period. Panel C is the sort of the second order of Enterprise Value (EV) during the past t-period.

Panel H	Alpha	MKT	SMB	HML	Panel I	Alpha	MKT	SMB	HML
12-month	0.394	-0.018	-0.191	-0.511		-0.169	0.023	0.265	0.385
	[2.48]	[-0.46]	[-3.40]	[-8.47]		[-1.10]	[0.62]	[4.90]	[6.64]
24-month	-0.169	-0.082	0.407	0.673		-0.004	-0.058	0.320	0.601
	[-1.10]	[-2.23]	[7.53]	[11.63]		[-0.02]	[-1.65]	[6.28]	[10.99]
36-month	-0.001	-0.121	0.419	0.696		0.142	-0.107	0.393	0.679
	[-0.01]	[-3.49]	[8.27]	[12.78]		[1.02]	[-3.21]	[8.06]	[12.95]
48-month	0.001	-0.163	0.386	0.810		0.146	-0.186	0.347	0.654
	[0.01]	[-5.42]	[8.60]	[16.75]		[1.13]	[-5.98]	[7.70]	[13.43]
60-month	-0.004	-0.148	0.238	0.844		0.207	-0.176	0.241	0.609
	[-0.32]	[-4.96]	[5.53]	[18.21]		[1.70]	[-5.97]	[5.67]	[13.31]

Panel J	Alpha	MKT	SMB	HML
12-month	0.107	-0.044	-0.18	-0.118
	[1.23]	[-2.10]	[-5.89]	[-3.59]
24-month	0.065	-0.075	0.189	0.125
	[0.70]	[-3.36]	[5.85]	[3.57]
36-month	-0.006	-0.024	0.132	0.174
	[-0.06]	[-1.06]	[4.09]	[5.01]
48-month	0.037	0.044	0.127	0.120
	[0.40]	[2.02]	[4.07]	[3.56]
60-month	-0.008	-0.002	0.144	0.211
	[-0.07]	[-0.07]	[3.88]	[5.25]