A FRESH PERSPECTIVE ON U.S. MUTUAL FUNDS' PERFORMANCE ATTRIBUTION, FACTOR MODEL AND QMJ

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Abstract

In this paper we evaluate the performance of the US mutual fund industry over the past 15 years, using a novel methodology developed by AQR Management's Quality Minus Junk paper (2013). We augment the standard regression models of Fama-French used in the literatures with a new factor, the Quality Minus Junk factor, which is a quality-ranking factor developed by the AQR Management. (Quality Minus Junk) 2013 Previously, conflicting evidence was recorded with regard to the merits of the mutual fund industry, and we believe this could be a result of the preceding researches were constructed based on the Fama–French three-factor model (FFM) and its various variations. Despite the FFM's prominent position in the asset-pricing field, it is subject to one critical limitation when it comes to evaluating active returns; no meaningful factor to directly quantify and evaluate the effects of active returns, as all existing factors are systematic in nature while active returns are idiosyncratic in nature largely. By incorporating the QMJ factor in the FFM framework, we hope to help investors better understanding their actively managed portfolios, as this unique factor is constructed based on four profoundly used fundamental metrics by the investment industry. We are still unable to use this factor to underpin the mutual industry as our results exhibit inconsistencies in the QMJ loadings despite QMJ's strong statistic and theatrical supports. Adding the Market-Factor results in the QMJ factor insignificant 70% of the time, adding more of the standard-factors we see that only 50% of the time the QMJ loadings are significant, around 40% of the time the QMJ loadings are in the negative zone. Therefore, we believe this shows inconsistence in QMJ's factor loadings. Furthermore, we identified consistent alphas (intercepts) in our regressions and we believe that combining Fama-French and QMJ factor still cannot explain all returns variations.

Executive Summary

This thesis provides an analysis and evaluation of the US mutual fund performance, and the investment styles they typically use.

Previous mutual performance studies suggest that there is mixed evidence to support mutual industry as some studies claimed that excessive returns above benchmarks is function of luck, while others found evidence that the very top performers tend to remain in their rankings. A through study of the leading factor models in the field of Asset Pricing Theory indicates that these models concentrate on systematic factors, but active returns should to be a function of non-systematic factors; specific investment managers' skills and experience to select quality companies. Therefore, we should include an additional quality factor to the existing models if we want directly evaluating active returns.

We follow the methodology of AQR Management who developed a new factor called Quality Minus Junk factor (QMJ). This paper demonstrates that using this special factor they were able to generate retrospect high excessive risk adjusted return, which is not directly explained by the systematic factors found in FFM and its existing variations. We apply this factor in the context of mutual fund performance evaluation analysis. We combine QMJ factor with the standard three and four factor Fama and French models. Our analysis employs monthly data, and our specifications are adjusted for fixed effect to control for firm and portfolio specific effects in our estimation. Risk premiums are calculated by subtracting risk free rates away, and risk free rates are historical monthly data on 90-day T-bill yield US Treasury bill rates.

We performed six separated sets of regressions with fund returns as dependent variables; 1) fund returns with QMJ, 2) fund returns with QMJ and Market, 3) fund

returns with SMB, HML, and Market, 4) fund returns with SMB, HML, Market and QMJ, 5) fund returns with SMB, HML, Market and the UMD (Momentum factor), 6) fund returns with SMB, HML, Market, UMD, and QMJ.

The regression results are presented in the appendices from Table 1 to 6, and Graph 1, 2, 3, and 4. The estimation results show that there is no meaningful improvement in regression R-squares by adding the QMJ factor to the standard factor model and there is not consistence in QMJ factor loadings as some showing positive while others showing negative values. Moreover, 50% of all the QMJ loadings appear to be insignificant at 5% significance level except in first set of regressions where QMJ is the only independent variable. Therefore, we conclude that is no clear evidence to support the hypothesis that mutual funds as active investors tend to focus on quality companies. One interesting finding suggests that the QMJ factor and Market factor and other systematic factors tend to behave differently.

However, there is also strong evidence to support alphas across all regression as the intercepts of all regressions are almost significant except a few, and they are ranging from -0.05 to 0.06, following the same orders of the worst performing funds to the best performing funds. This could suggest that US mutual fund managers apply techniques other than quality selection or their metrics for quality selection are different from our QMJ factor. These alphas represent their uniqueness, as they cannot be explained by the factors we include in our regressions.

Some of the limitations: the finding only pertaining to US mutual fund industry, only 15 years of data were included in the analysis but the US mutual industry has been around more than a few decades, combining FFM with QMJ might not be the best description of reality. As our data including 2008 -2009 crisis, during the crisis all investments were sold regardless their quality due to liquidity constrains, this period data could have screwed our analysis. We think future study could exclude this extreme period. Furthermore, we suggest that more research needed to conduct to refining the QMJ factor, to test against more countries' mutual fund industries, to avoid sampling problem by only including the truly active funds, and perhaps further exploring the empirical and theoretical reasons behind the negative relationship between QMJ and other systematic factors.

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1: Introduction

The primary focus of this research is to modify the existing FFM with an intuitive quality factor that can help us better understanding the active mutual fund industry. Previous studies have provided us with a lot of evidences to repudiate the active mutual fund industry, as their performance appeared to be inconsistent and lacklustre. Evidence shows that there is no much performance persistent, i.e. this period's winner are not more likely to be the next period winners, and also some previous studies demonstrate that excessive returns above benchmarks is a just a function of luck. However, the fact that most of the previous studies were constructed by employing the FFM or its variations concerns us in two ways; first, the FFM congenitally lacks strong theoretical support despite high degree of goodness of fit, second, existing FFM variations also cannot directly measure active manager's skills. Most active managers claim that they apply the concept of "quality at a reasonable price" approach throughout their investment process as they intend to invest in quality companies in pursuit of active returns. Therefore, we believe that FFM's second shortcoming is particularly acute amid previous studies, as there is no way directly measuring the relationship between returns and quality without a factor accounted for quality. Without a clear picture of this imperative relationship it would be very difficult to evaluate and pinpoint mutual fund's performance accurately.

Our primary contribution is to the asset price theory as we have modified the FFM with an additional QMJ factor, which is intuitive as it is driven by reversing engineering the famous Gordon Growth Model, and it is also statistically consistent as AQR management in their research paper demonstrated that superior risk adjusted returns can be registered in retrospect.

The paper should also greatly benefit retail investors, mutual funds, hedge funds and pension funds. Small retail investors should only invest in an actively managed product if activism yields high benefits. If the performance of an actively managed product is indifferent from the underlying benchmark retail investors should be reverting to ETFs or other passive vehicles for cost saving. By incorporating this factor into their analysis, they should be in a better position to their investment judgements. Institutional buy side firms can also utilize this QMJ factor to guide through their management selection process.

According to financial theory, quality of a business can be attributed to four broad categories; profitability, growth prospect, Safety, and stocks pay-out.

Profitability: Profitability can be decomposed into two dimensions; profitability based on accrual basis and cash flow basis. Profitability of a company indicates management's ability to efficiently use capital to create value to stakeholders.

Growth prospect: intuitively, good growth prospect should ultimately lead to high profitability, and thus high quality.

Safety: High safety ultimately translates to the high stability and low volatility of a business.

Stock Pay-out: Finally, higher and healthy stock pay-out should indicate manager's confidence of a business, and also reduces agency-problem. Therefore, high payout should also lead to higher prices in the long term.

Our methodology is analogues to Jagadeesh and Titman's (1993)'s approach as we modified the FFM with an extra QMJ factor, and then applied factor model analysis to evaluate mutual fund’s historical performance. If we can successfully establish the relationship between returns and their exposure to the QMJ factor exposure, we can then conclude that mutual fund managers are capable of selecting quality companies or include quality in the investment process. In turn, this could establish some basis for supporting the active mutual fund industry. Alternatively, we should be reverting to other four explanations; 1) QMJ is too rudimentary and fails to capture other important quality determinates, 2) mutual funds focus on other areas other than actively selecting quality companies, 3) there could be other strategies that mutual fund employ to produce superior returns, 4) we concur with the previous studies that active managers are incapable of generating above benchmark returns.

Research interpretations

Since the AQR management clearly demonstrated (that’s one study, you need more research to determine how successful this factor is.) that QMJ factor portfolio could be used to generate high active returns in American stock market, and hence it should help us to verify whether active managers attempt to outperform their relative benchmarks by selecting quality stocks. In addition, the recent published paper, “Digesting Anomalies” (2012), discovered a Q-Factor, similar to the QMJ factor but only focuses on investment patterns and profitability, and it was subsequently confirmed by F. Fama and Kenneth R. French in 2013 that applying this additional factor almost all the unexplained average returns for individual portfolios are almost zero.

Despite our extensive statistical analysis, we could not find sufficient evidences to support active investment through the lens of the QMJ factor’s loadings. There appear to be a lot of inconsistences in terms of QMJ factor loadings across our analysis as some results suggesting negative loading. Negative loadings imply that some funds actually long low quality stocks while negatively exposing themselves to high quality ones. Across the board, as we adding more systematic factors to our regressions, QMJ factor does not seem to be very significant as 50% of the loadings become insignificant at 5% level at. However, one interesting note is that the QMJ factor appears to correlate negatively with the market and other conventional systematic risk factors, and thus inclusion of it could potentially lower portfolio systematic risk. Furthermore, we confirmed with previous studies that market factor is one of the most important sources to explain investment returns as we added Market factor into our model, initially it significant increased R-Squares by almost 30%-35% when we just added market to the standalone QMJ model. Other factors; SMB, HML, and UMD appear to be significant while the supporting evidence is not as strong as the market factor; SMB and HML appear to be significant 60% to 70% of the time, and UMD appears to be significant 70% to 80% of the time. This suggests that not all mutual funds in the US have a value and small cap bias, and many funds appear to follow the Momentum approach by clinching on or following previous winners. Although, we could not find sufficient evidences to support active investment, we are still not in a position to repudiate the hypothesis that active mutual fund can provide a better risk and reward profile for investors as other techniques could be employed to generate better results. Furthermore, we could have omitted other important factors that should be accounted for quality, and this could jeopardize our analysis and interpretations. Furthermore, whether the original FFM is a fair representation of the reality is still questionable, and thus the failure of not seeing consistent results could be as result of other FFM factors.

The remainder of this paper is organized as following; section 2 will our research methodology, in section 3 we will present all the descriptive statistics and data results, section 4 will include our conclusion remarks, and finally section 5 will list all the references we have in this paper.

Furthermore, we found an additional piece of interesting evidence that all the regressions' alphas appear to be statistically significant except a few. Alphas vary from -0.04 to 0.055 monthly in the first QMJ only regression (Table 1), and when market factor is included they are reduced systematically but becoming more significant (Table 2). As we gradually include more systematic factors in our regressions, these alphas do not reduce much and still very significant at 5% significance level. More importantly, because we rank our portfolios according to their lagged performance, the better than ranking the better the average alpha, while the previously worst 50% performing funds tend to have a negative alpha. There are about 50% of the portfolios' alphas in positive and the other 50% in negative. Moreover, the average alpha across these 10 portfolios of funds is almost zero in every set of regressions except the first set where our regressions only include the QMJ factor. This could possibly imply that while collectively there are indifferent from their benchmarks (not outperforming as a group), top groups of funds can generate positive alphas for the reasons yet to determine. It is important to note that some managers claim they can systematically time the market, and some managers can use other unconventional investment techniques to outperform the market. If quality selection process cannot fully explain these alphas, they could be a result of managers' unique investment skills. Alternatively, perhaps our QMJ factor is too rudimentary to capture all the quality metrics, for example industry competition, supplier concentration, buyer concentration are not included in our QMJ factor.

2: Previous Literature

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2.1 Asset Pricing

The essence of asset pricing is to explain how investors evaluate risks, and in turn how they determine what risk premium to demand collectively. Therefore, the risk premium or implied return determines the correct asset prices. Historically, US equity market has returned investors on average a whopping 9%, only 10% of that 9% is attributed to interest rates and the rest is a function of equity risk premium. Therefore, it is no surprise that modern financial economists and practitioners have spent a great deal of their time in studying what drive risk premium. The modern asset pricing began with the work of Markowitz (1959), he suggested that all investors allocate their capital rationally and mean variance efficiently. The notion of Mean-Variance portfolio was further developed in the 1960s by William Sharpe (1964), Jack Treynor (1962), and John Lintner and Jan Mossin (1965 -1966). As a result, CAPM famously emerged due to its strong theoretical structure. The simplicity of CAPM suggests that only one factor is required to explain all asset returns; that is the market factor. In other words, the market factor is the only source of uncertainty beside risk free rate. However, overwhelming evidences seemed to disprove CAPM despite it is widely applied as it has failed to explain asset returns and achieve statistical significance. (Black, Jensen and Scholes (1972) made one of the earliest empirical studies of CAPM, unfortunately, their estimations of slope and intercept are vastly different from the CAPM predictions) Perhaps, it is the stringent economic assumptions underlying CAPM invalidate it largely. As a CAPM failed to fit the empirical data, other theories were also developed which include APT by Ross (1976), Fama French Model (1992) and Supply-side Macroeconomic model by Chen, Roll and Ross (1986). Apart from arguing whether the proxy of market portfolio is efficient, there are two additional branches of studies attempt to explain why reality is drastically different from theories would suggest; 1) behaviour finance argues that there are behaviour factors we failed to include in our models and some are indeed deemed to be irrational in the eyes of orthodox school of thoughts, and 2) there are other systematic risk factors our CAPM misses. In the traditional view of economics and finance, irrational factors are not important in solving equilibrium models, assumed random and thus non-systematic. However, reality suggests otherwise, human behaviours exhibit irrational patterns, and thus the efficient market hypothesis partially depends on full rationality is indeed questionable.

As famously summarized by the Former Federal Reserve Chairman, Alan Greenspan, in his book of The Age of Turbulence; “But after several years of closely studying the manifestations of animal spirits during times of severe crisis, I have come to believe that people, especially during periods of extreme economic stress, act in ways that are more predictable than economists have traditionally understood. More important, such behaviours are measurable and should be an integral part of economic forecasting and economic policymaking. Spirits, it turns out, display consistencies that can help economists identify emerging price bubbles in equities, commodities, and exchange rates -- and can even help them anticipate the economic consequences of those assets’ ultimate collapse and recovery.” Moreover, he continues; “From the perspective of a forecaster, the issue is not whether behaviour is rational but whether it is sufficiently repetitive and systematic to be numerically measured and predicted."

Financial economists supporting the view of multi factors model think that CAPM has excluded other important systematic risk factors. Fama French (1993) discovered two additional factors that should be included to explain asset returns; value factor and size factor. Since then more factors have been introduced to make slight adjustments to the Fama and French three-factor model. In 1993, Jegadeesh and Titman have discovered that stocks performed well in the past outperformed stocks with past poor performance; Momentum effect. The momentum effect tends to imply that market is under reacting to information systematically. Despite the weak evidences for rational explanations, the Fama and French three factor model with high R square failed to explain the effect of momentum. On the other hand, Lakonishok, Shleifer and Vishny (1994) suggest that high returns are a consequence of investors' overreactions. Furthermore, they indicate that investors tend to ignore stocks with high B/M, and thus under researched by analysts. In 2009 Asbess, Moskowitz and Pedersen provide evidence that both Momentum and Value strategies are successful when applying in a range of asset classes; currencies, commodities, and bonds. In addition, a more recent study carried out by Kewei Hou, Chen Xue, and Lu Zhang, published in 2012, "Digesting Anomalies: An Investment Approach," suggested a new factor model that attempts to explain many of the anomalies that none of the previous models can do a good job to explain. The additional factors are investment and profitability; it is called "The q-factor Model". The major difference between this new approach and the previous ones is the introduction of two new beta dimensions: investment and profitability factors, which are widely accepted by the investment committee in terms of using it to judge stock performance. In the Fama &

French 2013 paper, five –Factor Asset pricing model, they used a set of empirical tests to verify if adding the profitability and investment patterns factor to their existing three factor model can yield a model that is superior to the old factor models, and they noted that “While the five- factor model does not improve the description of average returns of the four factor model that drops the HML, the five factor model may be a better choice in application. For example, through captured by exposures to other factors, there is a large value premium in average returns that is often targeted by money managers” Furthermore, they also state that “Unexplained average returns for individual portfolios are almost all close to zero.” Therefore, there are still more questions need to be answered before any conclusions can be made. Following the footsteps of these people, and using a new paper published by the AQR Capital Management as the foundation of our thesis, “Quality Minus Junk”, we attempt to provide an update of the paper published by its original authors by using data including 2015. In the “Quality Minus Junk” study, quality factor is further divided into four dimensions to further decompose the effects of the quality factor. Among the four quality factors, profitability is an important one although defined differently from the paper, “Digesting Anomalies: An Investment Approach,” we came up with evidences suggesting that this quality factor is important, and can earn significant higher risk adjusted returns with information ratio above one.

In this paper we will illustrate the logic behind the QMJ factor, and use this factor to modify the Fama & French model as we try to evaluate the US mutual fund industry performance in relation to the QMJ factor over the past 15 years.

2.2 Mutual Funds' Performance

In theory, active investors should perform differently from their benchmarks in order to achieve alphas. Economic theory suggest that active investors through buying and selling securities and sending pricing signals should enhance business efficiency overall, and thus growing the economic pie and obtain excess returns. However, it is observed by the investment world that alphas are difficult to get. The overall academic consensus is mixed with regard to the merits of mutual fund industry, but slightly skewed towards the notion that it is better off buying indexed funds as mutual funds' high management fees erode away any rare excess returns. Mark M. Carhart (1997), in their paper, on persistence in Mutual Fund Performance, suggest that common factors in stock returns and persistent differences in mutual fund expenses and transaction costs explain almost all the predictability in mutual fund returns. Classically, evidences from Jensen (1969) suggest that subsequent good performance does not follows previous superior performance, and more importantly, their evidences pointing towards the conclusion that those superior returns are mainly a function of luck. Several other subsequent research articles (e.g. Malkiel, 1995; Gruber, 1996; Carhart, 1997) also reconfirmed Jensen's findings. In light of the recent financial crisis, more studies have came out to demonstrate worse performance relative to their benchmarks by active funds during market downturns (e.g. Souza and Lynch, 2012; Pfeiffer and Evensky, 2012) More recently, an article published by the investment practitioners side of the business (Vanguard, 2009) discovers very little evidence in support of superior active management performance during market turmoil and stat that "in fact, active managers have not consistently delivered superior performance relative to a benchmark during such periods." Furthermore, Vanguard in 2009 shown that active fund managers failed to outperform broader stock market 4 out of

7 bear markets. However, reality is not always so black and white, particularly in the field of finance and economics a subset of social science, there are as much supporting active investment evidences as non-supporting evidences. For instances, using a sample of quarterly portfolio data, Grinblatt and Titman (1989) present evidences to support mutual fund positive abnormal performance especially in two categories; growth and aggressive growth funds. Later studies (e.g. Grinblatt and Titman, 1993; Grinblatt, Titman, and Wermers, 1995; Wermers, 1997) also suggested superior performance by actively managed mutual funds. However, it is worthwhile to notice that most of their findings in support of alphas are a result of using gross returns rather than net returns since our focus is on whether as an average investor should use mutual funds as the core portfolio building block. In addition, Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995) also find strong evidences of persistence in mutual fund performance over one to three year horizon, and ultimately attributed the persistence to "Hot Hand" or common investment effect. In the view of longer term persistence, Elton, Gruber, Das, Hlavka (1993), and Blake (1996) show that superior performance should be a result of stock picking skills and manager's information value. In particular, with respect to Hendricks, Patel, and Zeckhauser's (1993) hot hand effect, Mark M. Carhart (1997) present evidences to suggest that most can be attributed to Jagadeesh and Titman's (1993) one year momentum in stock returns. Furthermore, they stat that " funds that earn higher one year returns do so not because fund managers successfully follow momentum strategies, but because some mutual funds just happen by chance to hold relatively larger positions in last year's winning stocks." Explanations as why active mutual funds tend to underperform ranging from mean reverting evidences to over diversified effects from mutual fund industry. In Shawky and Smith (2005), they

suggest an optimal point of holdings and beyond which value would be destroyed as a consequence. This finding can be traced to several corporate finance studies that suggest business diversification result in value reductions on average. (E.g. Lang and Stulz, 1994) However, Sapp and Yan (2008) show that even focused funds tend to destroy values by underperforming. It is important to notice that not all evidences in the real worlds are repudiating active investment strategies.

Furthermore, much of the previous works related to mutual fund performance were carried out from the perspective of FFM and its closely related variations. We need a fundamental factor to measure active returns as majority of professional money managers claim that they make their investment selections based on the fundamental approach. The essence of the approach is to identify quality investments, which are undervalued currently. Therefore, we think the additional QMJ factor based on the four major quality factors, will capture this fundamental relationship.

3: Data and Methodology

In this thesis, portfolios of mutual funds (dependent variable) formed on lagged 1 year return is regressed to systematic risk factors (independent variables) to see if mutual funds can provide persistent excess return. Thus, we used two sets of data in this thesis to perform statistic test: Mutual Funds Data and Factors' Data.

3.1 Factors' data and Methodology

The data for factors used in this thesis are from the AQR'S homepage. It includes the three Fama & French four factors, market risk premium, SMB, HML and UMD; quality minus junk factors, QMJ; as well as the risk free rate with the one month US Treasury bill as a proxy. Since we can only obtain mutual funds data from U.S. market, we only used U.S. factor data from AQR's dataset. Please see table 7 in appendix for a summary of factors, as well as correlation between them.

All factor portfolios construction follows Fama and French (1992, 1993, and 1996) and Asness and Frazzini (2013) and Asness, Frazzini and Pedersen (2013).

3.1.1 Fama and French Four Factors

The Market factor MKT is the value-weighted return on all available stocks minus the one-month Treasury bill rate.

The size, value and momentum factors are constructed using six value-weighted portfolios formed on size and book –to-market and 1-year return. At the end of each calendar month, stocks are assigned to two size-sorted portfolios based on their market capitalization. The size breakpoint is the median NYSE market equity. AQR use conditional sorts, first sorting on size, then on the second variable and rebalance portfolio monthly to maintain value weights. They believe conditional sorts, which slightly different from Fama and French (1992, 1993, and 1996)'s independent sorts, ensure a balanced number of securities in each portfolio.

The size factor SMB is the average return on the 3 small portfolios minus the average return on the 3 big portfolios: SMB = 1/3(small value + small neutral + small growth) – 1/3(Big value + Big Neutral + Big growth).

The value factor HML follows Fama and French (1992, 1993, and 1996(. HML is the average return on the two value portfolios minus the average return on the two growth portfolios: HML = 1/2(small value + Big value) – 1/2(small growth + Big growth). To compute book to market ratios, AQR scale book equity (BE) by the total market value of equity (ME) at fiscal year-end.

The momentum factor UMD is the average return on the two high return portfolios minus the average return on the two low return portfolios: UMD = ½(small High + Big High) – ½(small Low + Big Low).

Each factor portfolios are value weighted; breakpoints are refreshed every month and rebalanced every month to maintain value weights.

3.1.2 QMJ factors

As the Quality Minus Junk Factor (QMJ) is the new factor in this thesis used to test mutual funds performance, we describe its data sources and the methodology for constructing quality measures in more details.

Pricing and accounting data are from the union of the CRSP tape and the Compustat/XpressFeed Global database. The U.S. data include all available common stocks in the merged CRSP/XpressFeed data. All portfolio returns are in USD and do not include any currency hedging. Excess returns are above the U.S. Treasury bill rate.

Quality Score

A variety of quality measures are used to identifying stocks of profitable, stable, safe and high payout companies. To avoid data mining, a broad set of measures are employed by AQR for each aspect of quality and average them to compute four composite proxies: Profitability, Growth, Safety and Payout. Then these four proxies of quality are averaged to arrive a single quality score.

Profitability is measured by gross profits over assets (GPOA), return on equity (ROE), return on assets (ROA), cash flow over assets (CFOA), gross margin (GMAR), and the fraction of earnings composed of cash (i.e. low accruals, ACC). To combine each measure, they must be standardized, which is done by converting each variable into ranks and then to get it z-score.

More formally, explained by AQR "let x be the variable of interest and r be the vector of ranks, Ri = Rank(Xi). Then the z-score of x is given by Z(x)=Zx=(r-Ur)/Dr, where Ur and Dr are the cross sectional mean and standard deviation of r. "

Thus, Profitability score is the average of the individual z-scores:

$$\textbf{Profitability} = \mathbf{Z(Zola + Zroe + Zroa + Zcfoa + Zgmar + Zacc)}$$

In a same way, Growth is measured as the five-year prior growth in profitability, then averaged to get a Growth proxy.

$$\textbf{Growth} = \mathbf{Z\ (Z\Delta gpoa + Z\Delta roe + Z\Delta roa + Z\Delta cfoa + Z\Delta gmar + Z\Delta acc)}$$

Safty is defined by low beta(BAB), low volatility(IVOL), low leverage(LEV), low bankruptcy risk (O-score and Z-core) and low ROE volatility (EVOL):

$$\textbf{Safety} = Z(Z_{bab} + Z_{ivol} + Z_{lev} + Z_{o} + Z_{z} + Z_{evol})$$

Payout is defined by Equity and debt net issuance (EISS, DISS) and total net payout over profit (NPOP):

$$\textbf{Payout} = Z\,(Z_{eiss} + Z_{diss} + Z_{npop})$$

Last, four quality proxies are combined into one quality score by averaging them:

$$\textbf{Quality} = Z(Z_{profitablility} + Z_{growth} + Z_{safety} + Z_{payout})$$

Once having the quality score, quality–minus-junk factors (QMJ factors) can be constructed by following Fama and French (1992, 1993, and 1996) and Asness and Frazzini (2013). By intersecting of six value-weighted portfolios formed on size and quality, stocks are assign to two size-sorted portfolios monthly based on their market capitalization. Size breakpoint is the median NYSE market equity. AQR use conditional sorts, first sorting on size, then on quality. Portfolios are value-weighted, refreshed and rebalanced monthly. The QMJ factor return is

$$\begin{aligned}\textbf{QMJ} &= 1/2\,(\text{Small Quality} + \text{Big Quality}) - \tfrac{1}{2}(\text{Small Junk} + \text{Big Junk}) \\ &= 1/2\,(\text{Small Quality} - \text{Small Junk}) + \tfrac{1}{2}(\text{Big Quality} - \text{Big Junk})\end{aligned}$$

3.2 Mutual Funds’ Data and Methodology

The data for mutual funds returns used in this thesis is from Center for Research in Security Prices Data base (CRSP). The programs Access, Excel and Matlab are used to clean and analyze the data. We choose to keep only the observations that are relevant to our research. Since previous research has covered periods before 2000, in this paper, the focus is for the period year 2000 to year 2014, thus observations before year 2000 are excluded and only data covering monthly value weighted returns are used. In addition, as result of availability, mutual funds data is from U.S. market only.

3.2.1 Cleaning data

To filter out outlier funds, only data for funds with net Asset value per share >0 and total net Asset value >100k is downloaded from CRSP mutual funds database. Since only pure equity funds are relevant, all funds with any debt holding are eliminated from sample data; funds with less than 10 percent of other assets is allowed and included in sample data to obtain enough observations. Next, we only keep funds with complete observations from 2000 to 2014 (180 observations) in the sample. Thus, funds closed or new commenced during the period are eliminated, as well as those with errors in return data. The result is 517 funds. Last, I further eliminated outliers that have monthly returns of top 2% or bottom 2% of all. The result is our sample covering 500 funds in U.S. Market, 180 month of observation for each.

3.2.2 One year lagged return

Our question is if Mutual funds' performance is persistent, that is, if one is a winner this year, if it is still a winner a year later. Thus, for each month, the funds' return data first subtract risk free rate for the month to get their risk premium and then sorted based on this risk premium from low to high. Next, based on this ranking, funds' 1 year lagged return is associated. As result of lagged return, we now have one year less of observations, which come to 84,000 of funds monthly return observations.

To make our sample data ready for fixed effects model, each fund's monthly return subtracts its mean monthly return.

3.2.3 Assign funds to 10 portfolios

Based on classic empirical testing approach, 10 portfolio of mutual funds are formed. Mutual funds are sorted every month from January 1, 2000 to Dec 31, 2013 into deciles portfolios based on their previous calendar year's return. The portfolios are equally weighted monthly. Funds with the highest past one-year return comprise decile 1 portfolio and funds with the lowest comprise decile 10 portfolio.

Now, we have our mutual funds data ready for testing.

3.3 Main Statistical Test

Mutual Funds' returns are strongly co-moved together. The fundamental source of the co-movement is hard to observe, not to mention to be measured. (Kritzman, 1993). Factor models are very useful in a situation where a few unobservable sources of systematic risk affect many random variables. The Fama and French four-factor model controls portfolios risk by managing its exposure to 4 common sources. In this thesis, we add one more common source of risk, quality. By discovering sources of risk, we might be able to control risk better. On the other hand, by examining funds' risk exposure; we can see how well funds perform in term of risk exposure; if adding more risk factor could help to explain funds' performance.

The method used in this thesis to analysis panel data for mutual funds' performance is by using fixed effect model. The method has been widely used to evaluate linear factor pricing models with panel data. We specify the sources of return co-variation, and then try to confirm whether these sources do indeed correspond to difference in return.

Fixed effect

In econometrics, a fixed effects model represents the observed quantities in terms of explanatory variables that are treated as if the quantities were non-random. Such models assist in controlling for unobserved heterogeneity when this heterogeneity is constant over time and correlated with independent variables. This constant can be removed from the data through differencing. Since it is reasonable to assume funds' return (dependent variable) is not random correlated with systematic risk factors (independent variables), we employ fixed effects models here. In panel data analysis here, we impose time independent effects for each entity that are possibly correlated with the repressors.

4: Results

Regression results for the 10 mutual fund portfolios can be seen in table 1, 2, 3, 4, 5, and 6. Regression results are from the past 15-year's monthly data from 2000 to 2014. We conduct our analysis by using monthly US Treasury bill rate as the model risk free rate. We perform our analysis without any currency exchange adjustment as we assume the perspective of an US-Dollar investor.

Table 1 presents the regression results obtained by regressing each portfolio's returns with only the QMJ factor alone. Surprisingly, QMJ appears to be negatively correlated with portfolio's returns and significant. While R-square is quite low hovering around 50%, this suggests that QMJ alone is not sufficient to explain portfolios' return variations and there should be other factors to explain their return variations. Alphas are mostly significant but with no sign of any consistence as 40% are in the negative territory and the other 60% are in the positive zone.

We combine the Market factor with QMJ in our regression analysis and present results in Table 2. Lo and behold, R-squares are significant higher than table 1's results by large margins almost by 40%, which could imply that the market-factor heavily influences these mutual funds on average. Average R-Square is around 92%. We plotted these two series of R-square in Graph 1, and as we can clearly observe that R-squares with just QMJ are dominated largely by the series that includes both the market and QMJ factor. In addition, all the market factor loadings are hovering around 1 plus and minus 0.15 and significant. This suggests strong evidence to support the market factor as it appears to be consistent, and all mutual funds have a positive exposure to market factor risk.

It is worth to mention that the QMJ factor appears to correlate less negatively with mutual fund portfolio's returns after including market factor in the regression analysis. Graph 2 shows that our QMJ coefficients with the Market factor are less negative than the QMJ coefficients without the market factor. This evidence suggests that there could be some degree of fixed effect as the market factor and the QMJ factor could be negatively related with each other. This finding is consistent with AQR Management results that QMJ factor tends to be negatively correlated with other systematic factors. However, assuming a significance level of 0.05, QMJ factor appears to be less significant as 7 out of the 10 portfolio's P-value are above the critical level, and this led us to accept the Null hypothesis that QMJ's coefficient is indifferent from zero.

Table 3 shows that mutual funds in the US do not appear to be strongly tilted towards either Small Cap or large Cap, and either value or growth style. We run a standard FFM Three-Factor-Model for each of the 10 portfolios and present our results in Table 3. At 5% significance level, there are only 5 portfolios with positive exposure to SMB and also statistically significant. At 5% significance level, there are 6 portfolios with positive exposure to HML factor and also statistically significant. While the consistence is slightly better for HML factor, we still do not have sufficient evidence to conclude that US mutual funds tend to be more value orientated. Furthermore, R-squares only have been marginally improved comparing with the results generated by the simple Market + QMJ regression model.

Table 4 presents the regression results of FFM Three-Factor-Model plus the QMJ factor. R-Squares are somewhat indifferent from the simple Three-Factor-Model's results, while this regression has slightly changed our impression of SMB factor, as 70% of the coefficients are now significant. This implies that QMJ cannot explain fund returns as other variables should be used. Majority of QMJ coefficients have turned to positive as Table 4 shows. Again, this shows that QMJ factor is somehow different from the systematic factors as shown in the Quality-Minus-Junk paper from AQR Management.

Table 5 shows the regression results after including the Momentum factor (UMD). We refer this as the Fama and French Four-Factor-Model. Including UMD in our analysis does not dramatically alter the regression results from Table 4. R-squares are quite alike the R-Squares generated from the Standard Three Factor Model. This implies that marginal explanatory power of the momentum factor is very low. However, 80% of UMD are significant and positive. This confirms with previous studies to suggest that mutual funds tend to in previous winners either passively or actively.

Table 6 shows the results of FFM Four-Factor-Model plus QMJ factor. While R-square stay relatively indifferent from the standard Four-Factor-Model alone, both UMD and SMB factor are significant as 70% of SMB and 80% of UMD factor loadings are significant at 5% significance level. This find is consistently with our understanding of the SMB factor's size effect; when comparing stocks of similar quality, small stock should outperform large stocks on average.

Table 1, 2, 3, 4, 5, 6, second column shows their respective regression's alphas. It is evident that they are almost all significant except one in the first table at 5% significance level. As we gradually increase more factors into the regression, their alphas systematically are reduced as shown in Graph 3. When including the Market Factor alphas are all reduced by a quite constant amount 0.075 approximately, this means that the ability of the market to explain return variations is significant and strong. As we added systematic factors into regression analysis we see that the alphas start to level out (Graph 3), with 50% in positive and rest in negative. These alphas are all significant and consistent with their performance rankings; the best performing funds tend to register higher positive alphas. This suggests a strong positive correlation between alphas and their performance rankings. Furthermore, these alphas demonstrate we have some evidence to believe that some funds are capable of generating above market returns due to unique reasons cannot be explained by the systematic factors and QMJ factor. Collectively, their average alpha appears to be close to zero, this confirms with previous studies that mutual fund industry as a group cannot outperform the market, but the high-ranking funds that can generate positive alphas perhaps at the expense of other active fund's underperformance as this could be a zero sum game or other reasons require further study.

Results conclusion

There is no sufficient evidence to suggest that mutual funds focus on quality investment as a mean to achieve excessive returns suggested by our regression results, while QMJ factor tend to behave differently from most market systematic factors. As suggested by ARQ'S QMJ paper and our regression results, QMJ appears to correlate negatively with the market factor. There is weak evidence that some mutual fund focus on small cap and value stocks. Consistent with both FFM and CAPM, it appears that the Market Factor is one of the most important factors in explaining mutual fund returns. Other systematic factors while seem to be significant cannot materially improve R-square. Finally, we found quite strong evidence to suggest that mutual fund industry as a whole tends to follow previous winners, but it is unknown to us whether they do it actively or passively. Moreover, evidence suggests that there is a strong positive correlation between fund's alphas and their corresponding rankings. Therefore, we believe that some funds are capable of generating positive alphas for specific reasons we do not know as our factors cannot explain this situation, while these returns cannot be explained my our quality factor. (QMJ)

5: Implications and Conclusions

In this paper we attempt to bridge Asset Pricing Theory that primarily focus on systematic factors with fundamental investment theory that focuses on actively scooping quality companies to achieve outperformance. Our goal is to use the integrated model to explain US active mutual fund performance.

conventional wisdom in the finance industry tells us that outperformance can be achieved by selecting quality investments at a reasonable low price. However, to the extent of what quality encompasses is quite blurry as different investors define quality slightly different depending upon their unique set of beliefs. It seems reasonable to assume that if a company grows at robust and sustainable rates, operates at high and steady profit margins, and disburses cash handsomely to its shareholders, the company is generally a quality company relatively to its peers. More importantly, these metrics are quantifiable with a reasonably degree of assurance. Therefore, QMJ factor is selected to rank companies as it encompasses all four quality metrics; safety, profitability, growth prospect, and pay-out ratio. If else equal, high quality firms should have higher scaled prices. AQR Management indicates that it is consistent with market efficiency theory; high quality firms do exhibit higher prices on average. However, the explanatory power of quality on prices is low, leaving the majority of cross sectional dispersion in scaled prices unexplained. Therefore, high quality firms exhibit high risk-adjusted returns. A quality-minus-junk (QMJ) factor that goes long high-quality stocks and shorts low-quality stocks earns significant risk-adjusted returns with an information ratio above 1 in the U.S. and globally across 24 countries. Therefore, we believe that the QMJ factor includes the necessary information for us to test mutual fund performance.

Our results present a puzzle for asset pricing and mutual fund performance, as we believe that we are not the first one to find conflicting evidence with regard to mutual fund attributions. Despite our high confidence in the QMJ factor, there is no consistent evidence to conclude that active managers as a whole tilted towards quality companies, as some QMJ factor loadings in our regression models are positive while others are negative, through most of these loadings are insignificant.

There are five major explanations to our findings.

1) Quality is differently defined in reality or the QMJ factor does not include all-important metrics pertaining to quality. Future studies should try to refine QMJ factor to include unique metrics pertaining to quality, and look for important factors that we have not yet quantified; industry competition, supplier and customer concentration, barrier of entry, and so called "Steve Job Effect".
2) Mutual fund industry uses a different set of techniques to capture excessive returns. It may be useful to re-categorize them according to their investment mandates, as each style is quite different from others.
3) Sample selection problem as a result of including all US available mutual funds. Some mutual funds can be self-proclaimed active but in fact passive. Therefore, it is necessary to separate real-active funds from the self-proclaimed active funds if one would like to find out the truth behind active mutual funds.

4) Collectively as a whole, the industry cannot select quality companies consistently but individual funds could, but they are buried beneath the average numbers. As we have mentioned in our literature review that the best active funds tend to be more consistent in terms of generating superior performance, but collectively as a group the negative ones might have neutralized the superior results. Mutual fund industry collectively represents a significant portion of all market assets, and as they are competing with each other, they skills would have been neutralized as a whole and reverting back towards benchmark returns.
5) QMJ and FFM may not fit well with each other, as the latter is a factor model includes mostly systematic factors. Therefore, QMJ factor should be concatenated with a different model.

6: Appendix

Table 1

10 portfolios' monthly returns against QMJ factor

Table 1	ALPHA	P-Value	QMJ	P-Value	R-Square Adjusted
P1	-0.034988	0.000000	-1.222320	0.000000	0.562598
P2	-0.014433	0.000000	-1.113460	0.000000	0.599680
P3	-0.006345	0.011002	-1.058786	0.000000	0.580683
P4	-0.000244	0.920331	-1.022867	0.000000	0.625683
P5	0.005243	0.030859	-0.993440	0.000000	0.599538
P6	0.010332	0.000023	-0.980911	0.000000	0.588692
P7	0.015885	0.000000	-0.977818	0.000000	0.570422
P8	0.022416	0.000000	-0.994747	0.000000	0.585677
P9	0.031844	0.000000	-1.047365	0.000000	0.592899
P10	0.054883	0.000000	-1.125732	0.000000	0.561942

Table 2

10 portfolios' monthly returns against QMJ factor and Market Factor

Table 2	ALPHA	P-Value	MKT	P-Value
P1	-0.043170	0.000000	1.048539	0.000000
P2	-0.022404	0.000000	1.021452	0.000000
P3	-0.014233	0.000000	1.010902	0.000000
P4	-0.008143	0.000000	1.012239	0.000000
P5	-0.002620	0.000007	1.007635	0.000000
P6	0.002617	0.000023	0.988619	0.000000
P7	0.008377	0.000000	0.962187	0.000000
P8	0.015142	0.000000	0.932140	0.000000
P9	0.024984	0.000000	0.879053	0.000000
P10	0.048694	0.000000	0.793124	0.000000

QMJ	P-Value	R-Square Adjusted
-0.134022	0.066483	0.822439
-0.053275	0.237204	0.914906
-0.009552	0.774160	0.938525
0.027755	0.302918	0.965023
0.052404	0.033122	0.978742
0.045196	0.083448	0.959460
0.020855	0.511159	0.948347
-0.027261	0.515677	0.949850
-0.134979	0.025230	0.920007
-0.302534	0.001191	0.855993

Table 3

10 portfolios' monthly returns against Fama-French-Three-Factor

Table 3	ALPHA	P-Value	MKT	P-Value
P1	-0.043822	0.000000	1.122171	0.000000
P2	-0.022914	0.000000	1.044742	0.000000
P3	-0.014543	0.000000	1.012402	0.000000
P4	-0.008303	0.000000	0.994042	0.000000
P5	-0.002716	0.000001	0.976711	0.000000
P6	0.002369	0.000034	0.955610	0.000000
P7	0.007806	0.000000	0.932923	0.000000
P8	0.014036	0.000000	0.915942	0.000000
P9	0.022983	0.000000	0.895639	0.000000
P10	0.045654	0.000000	0.864353	0.000000

SMB	P-Value	HML	P-Value	R-Square Adjusted
-0.013631	0.831000	-0.031881	0.581653	0.825431
0.032992	0.400781	0.024395	0.492568	0.916552
0.030416	0.290365	0.043412	0.096431	0.939070
0.033617	0.142884	0.061289	0.003472	0.965582
0.037100	0.070256	0.081181	0.000019	0.979108
0.065722	0.002315	0.087827	0.000009	0.960450
0.111161	0.000020	0.098950	0.000028	0.948284
0.174136	0.000000	0.115080	0.000180	0.952610
0.281529	0.000000	0.095815	0.029350	0.923030
0.411341	0.000000	0.000867	0.989985	0.855473

Table 4

10 portfolios' monthly returns against Fama-French-Three-Factor plus QMJ

Table 4	alpha	P-Value	MKT	P-Value	SMB	P-Value	HML	P-Value	QMJ	P-Value	R-Square Adjusted
P1	-0.042347	0.000000	1.035248	0.000000	-0.107299	0.154881	-0.030707	0.591234	-0.199069	0.023076	0.824947
P2	-0.022542	0.000000	1.022798	0.000000	0.009345	0.841645	0.024691	0.487523	-0.050257	0.353306	0.916119
P3	-0.014593	0.000000	1.015351	0.000000	0.033595	0.328392	0.043373	0.097676	0.006756	0.864850	0.939122
P4	-0.008748	0.000000	1.020273	0.000000	0.061883	0.023187	0.060935	0.003418	0.060073	0.056109	0.965462
P5	-0.003420	0.000000	1.018265	0.000000	0.081879	0.000636	0.080620	0.000012	0.095166	0.000597	0.979563
P6	0.001555	0.007549	1.003626	0.000000	0.117465	0.000003	0.087179	0.000005	0.109967	0.000136	0.960980
P7	0.006956	0.000000	0.983087	0.000000	0.165218	0.000000	0.098273	0.000019	0.114884	0.000890	0.949603
P8	0.013288	0.000000	0.960030	0.000000	0.221645	0.000000	0.114484	0.000165	0.100968	0.026905	0.953244
P9	0.022624	0.000000	0.916825	0.000000	0.304359	0.000000	0.095529	0.030059	0.048520	0.466324	0.922565
P10	0.046070	0.000000	0.839878	0.000000	0.384966	0.000038	0.001198	0.986198	-0.056053	0.594910	0.855769

Table 5

10 portfolios' monthly returns against Fama-French-Four-Factor

Table 5	ALPHA	P-Value	MKT	P-Value	SMB	P-Value	HML	P-Value	UMD	P-Value	R-Square Adjusted
P1	-0.044309	0.000000	1.166663	0.000000	-0.003358	0.956919	-0.018788	0.738900	0.102521	0.000975	0.824431
P2	-0.023212	0.000000	1.071974	0.000000	0.039279	0.304389	0.032408	0.349889	0.062749	0.001018	0.919640
P3	-0.014815	0.000000	1.037277	0.000000	0.036159	0.188987	0.050732	0.042803	0.057318	0.000035	0.940629
P4	-0.008535	0.000000	1.015230	0.000000	0.038509	0.077373	0.067525	0.000738	0.048823	0.000009	0.965981
P5	-0.002918	0.000000	0.995144	0.000000	0.041356	0.034291	0.086605	0.000002	0.042474	0.000015	0.980414
P6	0.002202	0.000075	0.970856	0.000000	0.069242	0.000981	0.092313	0.000002	0.035130	0.000692	0.967487
P7	0.007629	0.000000	0.949085	0.000000	0.114893	0.000007	0.103706	0.000008	0.037241	0.002678	0.952777
P8	0.013845	0.000000	0.933334	0.000000	0.178151	0.000000	0.120197	0.000078	0.040074	0.013930	0.960893
P9	0.022769	0.000000	0.915167	0.000000	0.286038	0.000000	0.101562	0.020400	0.044998	0.057860	0.934696
P10	0.045419	0.000000	0.885828	0.000000	0.416299	0.000000	0.007187	0.917202	0.049483	0.188567	0.865533

Table 6

10 portfolios' monthly returns against Fama-French-Three-Factor plus Momentum factor & QMJ

Table 6	ALPHA	P-Value	MKT	P-Value	SMB	P-Value
P1	-0.042626	0.000000	1.068804	0.000000	-0.112162	0.123839
P2	-0.022705	0.000000	1.042484	0.000000	0.006491	0.886216
P3	-0.014737	0.000000	1.032708	0.000000	0.031079	0.343674
P4	-0.008865	0.000000	1.034411	0.000000	0.059834	0.021096
P5	-0.003518	0.000000	1.030054	0.000000	0.080170	0.000474
P6	0.001477	0.009305	1.013005	0.000000	0.116106	0.000002
P7	0.006873	0.000000	0.993049	0.000000	0.163774	0.000000
P8	0.013197	0.000000	0.971019	0.000000	0.220052	0.000000
P9	0.022515	0.000000	0.929936	0.000000	0.302459	0.000000
P10	0.045939	0.000000	0.855598	0.000000	0.382688	0.000040

HML	P-Value	UMD	P-Value
-0.016249	0.769026	0.111639	0.000290
0.033174	0.337663	0.065496	0.000645
0.050851	0.042901	0.057743	0.000036
0.067027	0.000773	0.047036	0.000019
0.085699	0.000001	0.039221	0.000044
0.091220	0.000001	0.031203	0.001895
0.102565	0.000006	0.033145	0.006376
0.119220	0.000078	0.036562	0.024313
0.101179	0.021157	0.043622	0.068060
0.007971	0.908356	0.052300	0.167937

QMJ	P-Value	R-Square Adjusted
-0.233179	0.006323	0.823869
-0.070268	0.184028	0.920472
-0.010887	0.775234	0.940272
0.045702	0.128217	0.966233
0.083183	0.001753	0.980386
0.100433	0.000369	0.967342
0.104757	0.002103	0.952668
0.089797	0.047471	0.960713
0.035192	0.596850	0.936995
-0.072033	0.495988	0.871812

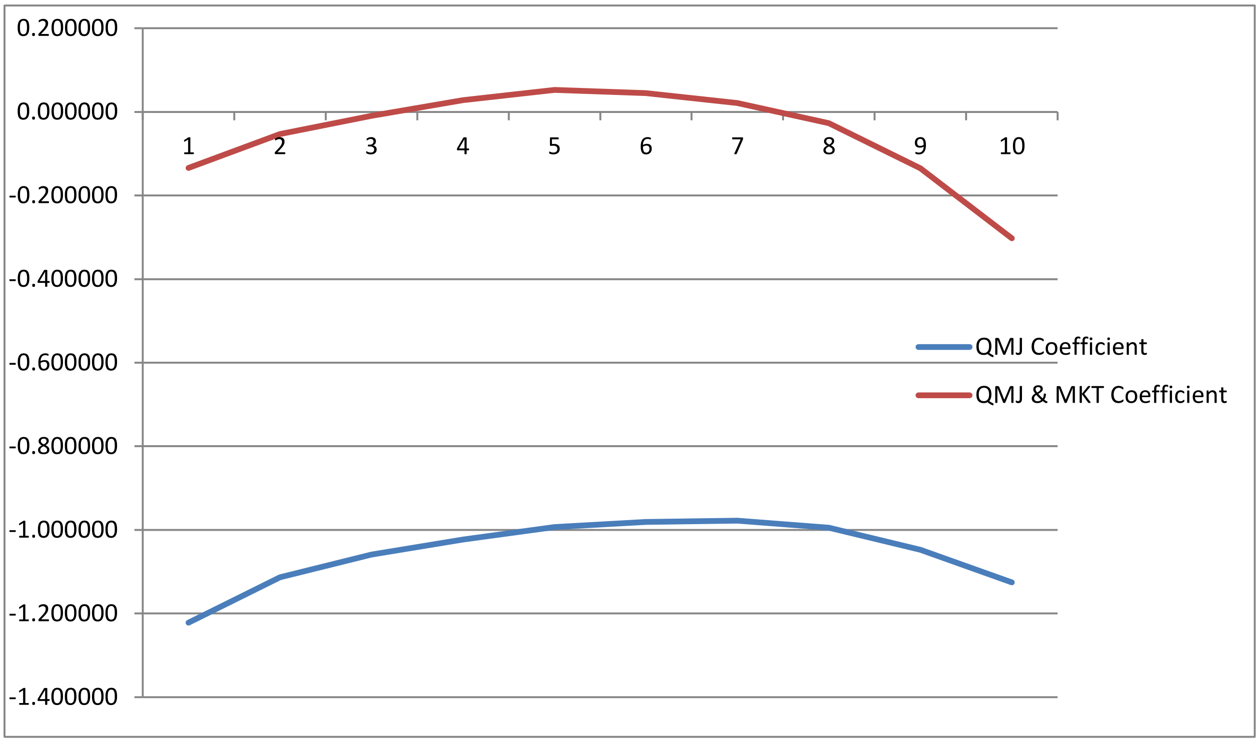
Table 7

Factors' Summary and Correlations

Factor Portfolio	*Monthly Excess Return*	*Stud Dev*	*t-stat for Mean =0*	*MKT*	*SMB*	*HML*	*UMD*	*QMJ*
MKT	0.47%	4.62%	1.317	1				
SMB	0.42%	2.51%	2.157	0.3976	1			
HML	0.22%	2.56%	1.137	-0.0014	0.0288	1		
UMD	0.16%	5.46%	0.379	-0.4776	-0.4080	0.1370	1	
QMJ	0.30%	3.02%	1.284	-0.7926	-0.5307	-0.0977	0.6090	1

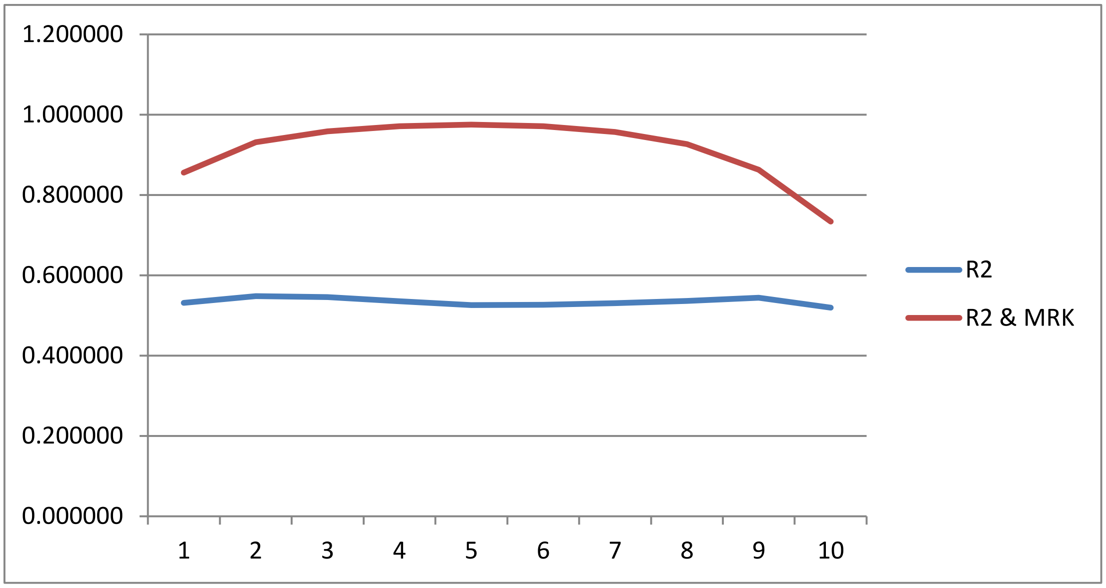
Graph 1

Plotting two sets of regressions QMJ factor loading; 10 portfolios' returns against QMJ, and 10 portfolios' against QMJ and Market factor.



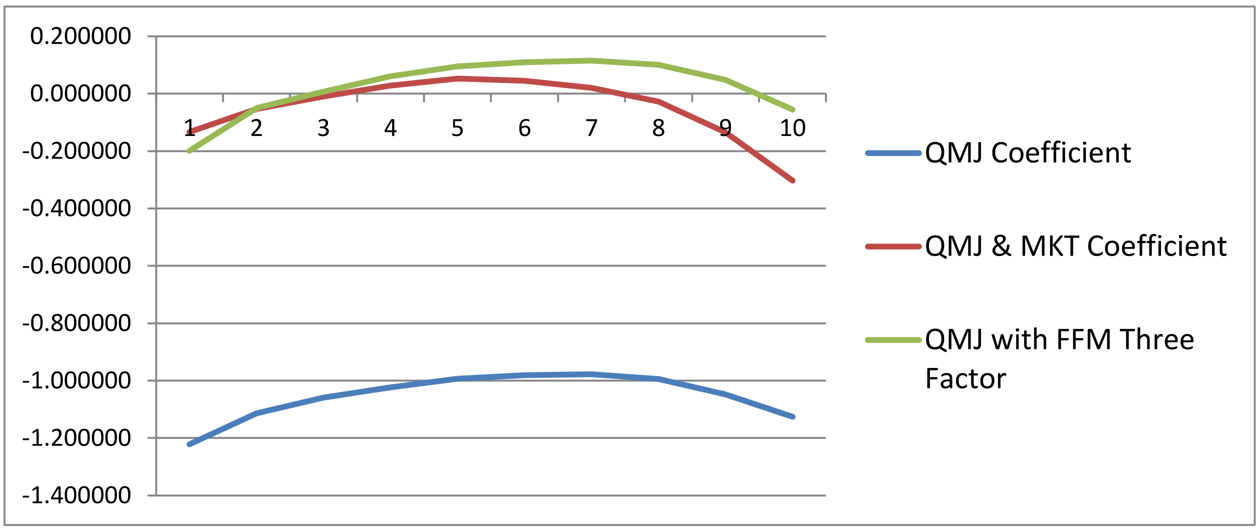
Graph 2

Plotting each regression's R-squares, two sets of regressions' R-Squares are plotted; 10 portfolios' returns against QMJ, and 10 portfolios' against QMJ and Market factor.



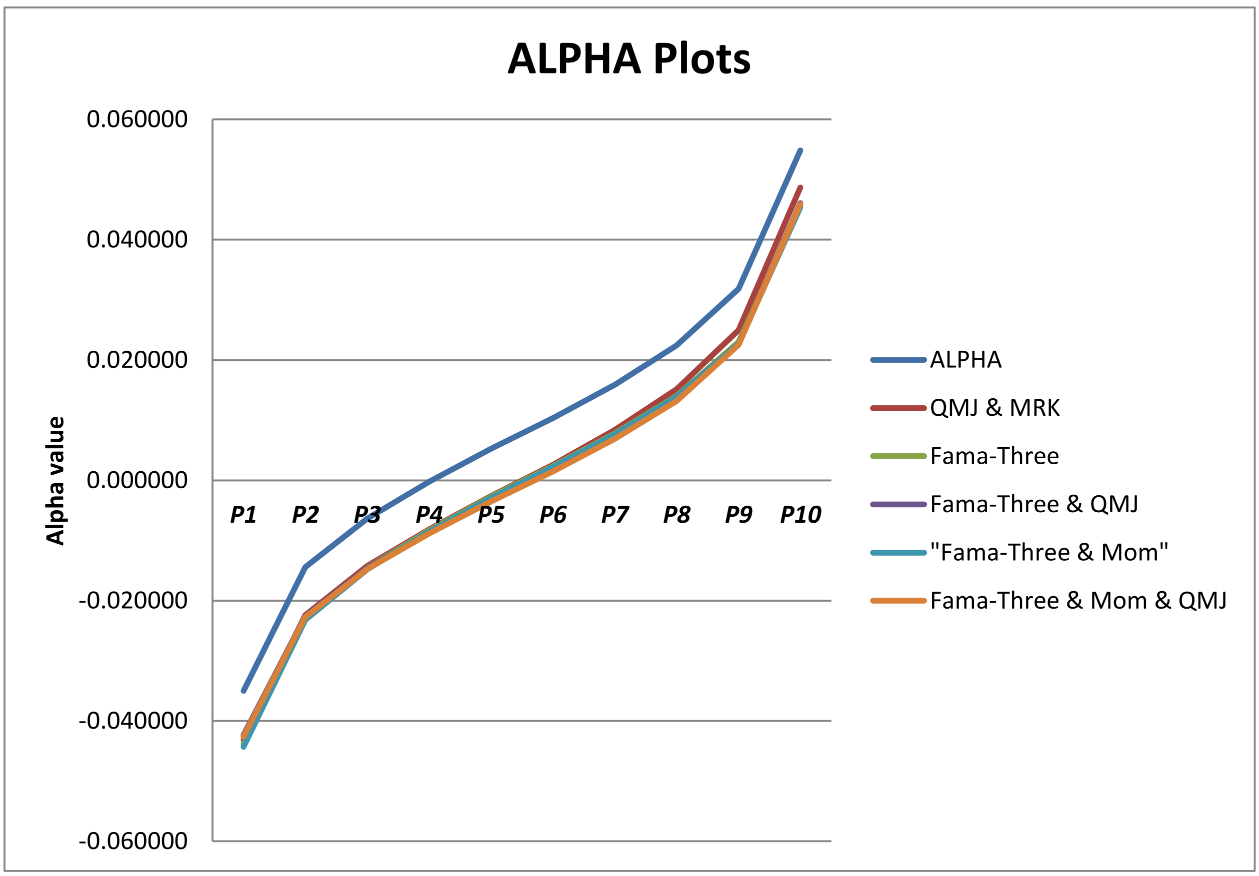
Graph 3

Plotting each regression's R-squares, three sets of regressions' R-Squares are plotted; 10 portfolios' returns against QMJ, 10 portfolios' against QMJ and Market factor, and 10 portfolios' against Fama – French -Three Factor and QMJ



Graph 4

Plotting all alphas generated from the six sets of regressions: Mom stands for Momentum factor, MRK stands for Market Factor, QMJ stands for Quality Minus Junk Factor, and Fama-French-Three Factor includes, Size Factor, Value Factor, Market Factor.



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