The Impact of Fama-French Factors on Portfolio Returns

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Abstract: The purpose of this regression analysis paper is to confirm and build upon the findings of Eugene Fama and Kenneth French and their renowned three-factor model by using a portfolio of momentum stocks. In this paper, a linear model is constructed from the returns of the top 200 performing stocks in the Russell 300 index over 250 consecutive trading days. Dependent variables such as risk, size, and book-to-market value are measured and evaluated with respect to their impact on returns. The results of this study indicate that the Fama-French three-factor model expands significantly on the capital asset pricing model and a two-factor model in predicting abnormal returns of momentum at a more significant level.

Keywords: Portfolio Regression, Fama and French, 3-Factor Model, Momentum, Expected Returns, Efficient Market Hypothesis

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1. Introduction

This regression analysis was conducted in order to determine how much of the return of a momentum-based portfolio can be explained by the size of the stocks, the book-to-market value of the stocks, and the risk inherent within the market.

We used Bloomberg Terminals to find data for the historical returns of a sample portfolio composed of securities from the Russell 3000 stock index. This sample portfolio screened the stocks from the Russell 3000 to find the top 200 stocks with the most momentum. Momentum is defined as the tendency of stocks that perform well over a formation time period (defined as t to t-12 wherein t is the current month) relative to stocks that perform poorly will continue to perform well in the future relative to stocks that perform poorly. Deriving a portfolio based upon the theory of momentum allows us to analyze stocks that are expected to do well in the future. Thus, for this project, we will be able to determine whether there is a relationship between equity risk (B_1), stock size (B_2), and stock book-to-market value (B_3) on the dependent Y-variable: Portfolio Return.

After we composed a portfolio of the top 200 stocks exhibiting momentum in the Russell 3000 index, we will regress the daily returns of the portfolio over the previous year with Fama-French factors published by in the Kenneth R. French Data Library. Fama & French list the following factors as explanatory variables of portfolio return: equity risk premium (return of the market minus return of a riskless asset), size (the amount by which small-cap stock returns are expected to exceed large-cap stock returns), and value (the amount by which the returns of high book-to-market ratio, value, stocks are expected to exceed the returns of low book-to-market ratio, growth, stocks). These factors are listed on a daily, weekly, and monthly basis from 1926 to the present day. We will be regressing daily returns of our portfolio against the daily factors composed by Fama & French from February 15th 2018 to February 20th 2019.

This regression is significant as it will evaluate the findings of Eugene Fama and Kenneth French, who claimed that the three factors which have the greatest influence on portfolio returns are (1) market risk, (2) performance of small size stocks over large, and (3) performance of value stocks over growth stocks. In academia, there is widespread debate as to whether the Fama-French model invalidates the previously accepted capital asset pricing model, CAPM, or whether it simply adds further layers of explanatory variables.

CAPM: $r_i = b_0 + (r_M - r_{RF})b_1$

Fama-French Three-Factor Model: $r_i = b_0 + (r_M - r_{RF})b_1 + (r_{SMB})b_2 + (r_{HML})b_3$

Additionally, the results of this regression have implications on the efficient-market hypothesis, which theorizes that the value of all assets take into account all information available. In other words, it is impossible to "beat the market" through arbitrage (ex. Taking advantage of pricing mismatches with no risk). Thus, according to this theory, it is only possible to achieve greater returns by taking on greater risk or by pure chance. By performing this regression, one could determine which variables truly impact portfolio returns, or whether, as previously assumed, risk is the predominant variable which impacts return.

2. Literature Review

Before diving into the literature, it is necessary to discuss the seminal paper by Fama and French (1992), *The Cross Section of Expected Stock Returns* (also known as the "beta is dead" paper). In this paper, Fama and French find that there is a weak relationship between Beta (the volatility of a stock) and returns. This had notable implications on previous research, as many financial and economic professionals strictly adhered to the Capital Asset Pricing Model (CAPM) which claimed there was a direct, positive correlation between the riskiness of an asset and its returns. Instead, Fama and French (1992) posited a three-factor model which could explain as much as 95% of the returns of a diversified stock portfolio: size of underlying firm, value vs. growth companies, and risk (beta).

As such, it is necessary to understand the underlying drivers of returns. Finance professionals define value stocks as firms with high ratios of book-to-market (B/M), earnings-to-price (E/P), or cash flow-to-price (C/P). Fama and French (1997) claim that the outperformance of these "value" stocks over "growth" stocks can be attributed to risk not accounted for in the CAPM. On the other hand, Lakonishok et. al. (1994) and Haugen (1995) argue that the value premium in returns arises as the market undervalues distressed stocks and overvalues growth stocks. In regards to size, Fama and French (1992) find that smaller firms tend to outperform larger firms. While the assertion by Fama and French (1992) is proven empirically, others such as Ferson and Harvey (1999) rejected the multi-factor model's ability to accurately estimate portfolio returns. They found that when adjusting for variables with time-varying parameters, the three-factor model did not explain the conditional expected returns of the portfolios.

The most important aspect of the Fama-French three-factor model is the measure of risk and its relationship to the expected returns of a given portfolio. In the capital asset pricing model, risk is defined as the degree of uncertainty on the return of an investment relative to the market as a whole. Fama and French expand upon this isolated definition of risk, factoring in measurements of risk related to the size of the firm as well as the risk associated with value vs. growth stocks. Debate arises as to whether CAPM is inherently a poor measurement of return, or whether it simply doesn't account for other important factors. Womack et. al. (2003) explain how volatility, diversification, and systematic risk all contribute to the return of an asset, concluding that the CAPM and the Fama-French models are both valuable tools used by investors. In contrast, Ang et. al. (2004) claim that highly volatile risk stocks with low returns cannot be attributed to size, book-to-market, momentum, and liquidity effects. This theory contradicts that of Fama and French, which posits that sorting portfolios by idiosyncratic volatility has no effect on returns.

Expanding upon the three-factor model, our regression incorporates momentum as a means of maximizing the accuracy of our model, as stocks with momentum will hypothetically continue to perform in the near future. Momentum investing theory posits that stocks that have performed well historically or in the formation period will continue to perform better relative to worst-performing stocks in the future. Jegadeesh and Titman (2001) underscore the importance of this momentum in generating strong returns, concluding that stocks which perform the best over a three-12 month period continue to perform well over the following three-12 months. Similarly, Clare et. al. (2015) suggested momentum should be used in conjunction with trend following or trend trading, where an investor buys as prices trend upwards and sell as prices trend downwards. By using trend following as an extension of momentum, investors are able to achieve the returns affiliated with momentum portfolios, but with reduced volatility and drawdowns. This is further validated by the work of Antonacci (2016) who claims that absolute momentum can enhance returns while also lessening volatility and drawdown.

Lastly, the work of Fama and French that is being tested in our regression analysis has implications on the debate around the efficient market hypothesis (EMH), or the idea that the prices of assets or stocks fully reflect all information available. In order to understand this debate, it is necessary to understand how the market defines risk. Historically, financial professionals have used the CAPM which associated the returns of a stock to its risk relative to the market. The work by Fama and French expanded upon this model, adding two other factors: size and book-to-market value to understand the returns of an asset or stock. While it is clear from the literature that Fama and French challenged the former CAPM, as with all models, there are certainly additional variables and measurement methods that can help explain the returns of a stock. The implications of these findings on the EMH is that assets and stocks may fully reflect all information available, but how that information is interpreted and used by investors may be subject to behavioral factors as well as incomplete information. This is perhaps why the debate continues, and even why Fama and French (2015) describe a possible five-factor model to better estimate returns, adding measurements for profitability and investment strategies to their original model to create a five-factor model.

3. Data Explanation

3a. Sample Portfolio Data Sourcing

The Russell 3000 is defined as a stock index that tracks the top 3000 stocks in the United States weighted by market capitalization. Market capitalization of a specific stock is calculated by determining the share price of that stock multiplied by the total shares outstanding in the public of that stock.

Examples of stocks contained within the Russell 3000 include: Microsoft (MSFT), Apple Inc (AAPL), Amazon.com (AMZN), Alphabet Inc (GOOGL), and Facebook (FB). The Russell 3000 is not only comprised of these well-known stocks but also smaller stocks that must have a market capitalization above $159.2mm. An example of such a stock would be DKS (Dick's Sporting Goods) which has a market capitalization of $3.42bn.

The data for the daily returns of each of the 3000 stocks within the Russell 3000 was exported from a Bloomberg Terminal. This data was provided in a .CSV format which was then edited to calculate daily return for stocks over the time period (formation period): 2/20/2018 – 2/15/2019. The excel formula used to calculate cumulative return of a specific stock is as follows:

=PRODUCT(Return on 2/15/18:Return on 2/20/19)-1

The PRODUCT function can be interpreted as the product of daily returns from 2/16/18 to 2/15/19. This formula was used to calculate the cumulative return of each of the stocks contained within the Russell 3000.

After calculating the cumulative return of each stock over the formation period, the stocks were organized in a list from the highest cumulative return to the lowest cumulative return. Once we had organized the stocks in the Russell 3000 based on highest to lowest cumulative return over the formation period, the 200 stocks with the highest cumulative return were chosen to be in the sample portfolio. In other words, this calculation was performed to determine the 200 stocks with the highest momentum in the Russell 3000. By choosing the top 200 stocks, we ensure sector diversity as these stocks operate in multiple sectors while also limiting the effects of idiosyncratic risk that may significantly affect the overall portfolio returns (an unknown independent variable that may create a bias).

To determine the sample portfolio and its total historical return, it was assumed that 1 share of each stock in the portfolio was held for the time period of each trading day (weekdays excluding national holidays) from 2/15/2018 to 2/20/2019. This is equal to 250 trading days' worth of data. Assuming that each of the 200 stocks comprised equal weighting in our portfolio (each stock was $1/200^{th}$ of the total portfolio), we were able to calculate the total portfolio return which amounted to 126.22% over the entire formation period. For the purpose of our regression, we find the total portfolio return every day for the formation period by summing the total daily return of each of the 200 stocks in the aforementioned time period (under the assumption that we hold these 200 stocks throughout the entire year).

The following table (Figure 1) shows a 5 stock sample of our total 200 stock sample portfolio. The first column indicates the stock ticker, the second column is a calculation of the stock's cumulative return over the formation period (PRET), the third column indicates the weighting of the specific stock in our total portfolio, and the fourth column indicates the weighted return which is the product of PRET and weighting. The total portfolio return for each day during the formation period will be our dependent variable for the regression.

Ticker	Momentum/PRET	Weighting	Weighted Return
TNDM	2543.54%	0.50%	12.72%
HEAR	816.60%	0.50%	4.08%
NIHD	729.77%	0.50%	3.65%
I	545.61%	0.50%	2.73%
CNDA	405.22%	0.50%	2.03%

Figure 1

3b. Fama-French Data Sourcing

The data used for our independent variables was sourced from the Kenneth R. French data library published by Dartmouth University. This file is obtained as a .CSV format from the following URL:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The following table (Figure 2) shows the Fama-French factors. The first column represents the date the factor was calculated and it is formatted as YYYYMMDD, the second column represents the equity risk premium or the market (Mkt) return less the risk-free rate (RF), the third column represents the small-minus-big (SMB) or size factor, the fourth column represents the high-minus-low (HML) or value factor, and the final column represents the risk free rate or the value of investing in a riskless financial asset (such as the 10 year treasury bill). Each of these factors, excluding the risk free rate, are the independent variables used to regress against the portfolio return in the Fama-French regression.

Finally, we also list the sample statistics of the Fama-French factors in Figure 3 below. The mean, standard deviation, minimum, maximum, and sum of all the Fama-French factors is also listed in Figure 3. Similarly, a correlation analysis of the Fama-French factors can be found below in Figure 4.

Date	Mkt-RF	SMB	HML	RF
20180102	0.85	0.36	-0.22	0.50%
20180103	0.59	-0.39	-0.21	0.50%
20180104	0.42	-0.26	0.24	0.50%
20180105	0.66	-0.34	-0.26	0.50%
20180108	0.19	-0.16	0.07	0.50%

Figure 2

	Mkt-RF	SMB	HML	RF
Mean	0.012	0.011	-0.042	0.008
Std Dev	1.062	0.524	0.606	0.001
Sum	2.900	2.750	-10.600	1.916
Count	250.000	250.000	250.000	250.000
Min	-3.450	-1.630	-1.690	0.006
Max	5.060	1.320	2.320	0.010

Figure 3

Correlation Analysis of Fama-French Factors

	Mkt-RF	SMB	HML
Equity Risk Premium	1		
Size	0.05970466	1	
Value	-0.4207305	-0.3091087	1

Figure 4

4. Regression Analysis

4a. Hypothesis Test

As we have already determined that there are significant linear relationships between the dependent variable, portfolio return, and the independent variables of risk, stock size, and book-to-market value, an evaluation of which variables are significant to include in this regression is below.

CAPM: $r_i = b_0 + (r_M - r_{RF})b_1 + \varepsilon$

For Stock Size: $H_o : \beta = 0, H_1 \neq 0$

T-Statistic (Risk) = $\frac{\beta_0}{SE_{\beta_0}} = 27.61$

Critical T = -1.97, |T stat| > critical t, Significant

	df	SS	MS	F	Significance F
Regression	1	1595.66651	1595.66651	762.3671336	1.3227E-77
Residual	248	519.074443	2.09304211		
Total	249	2114.74096			

Figure 5

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.60871663	0.09150504	6.652274	1.83181E-10	0.42849053	0.78894272
Mkt-RF	2.38430412	0.08635342	27.61099	1.32269E-77	2.21422452	2.55438372

Figure 6

Two-Factor Model: $r_i = b_0 + (r_M - r_{RF})b_1 + (r_{SMB})b_2 + \varepsilon$

For Stock Size: $H_o : \beta = 0, H_1 \neq 0$

T-Statistic (SMB) = $\frac{\beta_0}{SE_{\beta_0}}$ = 18.02

Critical T = -1.97, |T stat| > critical t, Significant

	df	SS	MS	F	Significance F
Regression	2	1890.46193	945.230963	1040.98919	4.499E-121
Residual	247	224.279032	0.90801227		
Total	249	2114.74096			

Figure 7

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.58654736	0.06028265	9.7299526	3.7733E-19	0.46781376	0.70528096
Mkt-RF	2.32300777	0.05697861	40.7698189	1.118E-111	2.21078185	2.43523369
SMB	2.08002801	0.11543957	18.0183285	6.58E-47	1.85265654	2.30739948

Figure 8

Fama-French Three-Factor Model: $r_i = b_0 + (r_M - r_{RF})b_1 + (r_{SMB})b_2 + (r_{HML})b_3 + \varepsilon$

For Stock Size: $H_o : \beta = 0, H_1 \neq 0$

T-Statistic (HML) = $\frac{\beta_0}{SE_{\beta_0}}$ = -11.26

Critical T = -1.97, |T stat| > critical t, Significant

	df	SS	MS	F	Significance F
Regression	3	1966.706427	655.568809	1089.40749	1.074E-141
Residual	246	148.0345306	0.60176638		
Total	249	2114.740957			

Figure 9

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.54828852	0.04919258	11.1457564	1.2679E-23	0.45139614	0.64518089
Mkt-RF	2.07874732	0.051210243	40.5924128	5.134E-111	1.97788085	2.17961379
SMB	1.73066703	0.098969896	17.4868025	4.7843E-45	1.53573056	1.9256035
HML	-1.0597932	0.094152281	-11.256161	5.5543E-24	-1.2452407	-0.8743458

Figure 10

4b. OLS Regression Tests

Figure 11

CAPM - OLS Reg.

Variable	**Coefficient**
Portfolio Return	(1)
Equity Risk Premium	2.384***
	(0.0864)
Alpha	0.609***
	(0.0915)
N	250
R-sq	0.755

Standard errors in parentheses
* p<0.10 ** p<0.05 *** p<0.01

Durbin-Watson Statistic:
(2,250) = 1.907

Figure 12

2-Factor Model - OLS Reg.

Variable	**Coefficient**
Portfolio Return	(1)
Equity Risk Premium	2.323***
	(0.0570)
Size Factor	2.080***
	(0.115)
Alpha	0.587***
	(0.0603)
N	250
R-sq	0.894

Standard errors in parentheses
* p<0.10 ** p<0.05 *** p<0.01

Durbin-Watson Statistic:
(3,250) = 1.912

Figure 13

Fama-French - OLS Reg.

Variable	**Coefficient**
Portfolio Return	(1)
Equity Risk Premium	2.079***
	(0.0512)
Size Factor	1.731***
	(0.0990)
Value Factor	-1.060***
	(0.0942)
Alpha	0.548***
	(0.0492)
N	250
R-sq	0.930

Standard errors in parentheses
* p<0.10 ** p<0.05 *** p<0.01

Durbin-Watson Statistic:
(4,250) = 1.991

4c. Time-Series Regression Test

Simple Three Factor Econometric Model: $r_t = b_{0t} + (r_{Mt} - r_{RFt})b_1 + (r_{SMBt})b_2 + (r_{HMLt})b_3 + \varepsilon_t$

Critical Values for Durbin Watson: 5% Level, K=3, N=250

Lower Level: 1.777, Upper Level:1.809

Econometric Model (Lags)	$DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2}$	**Test for Significance**
No lag Model	1.991	**No autocorrelation, DW>UL**

Figure 14

As there was seemingly no autocorrelation given the results of the Durbin-Watson test, there was no need to perform lagged regression tests against the independent or dependent variables.

Is there Autocorrelation? While it may initially seem that a portfolio constructed on momentum analysis will contain high levels of autocorrelation, it is not always the case in practice. There are many theories that explain momentum as explained previously, including but not limited to: future returns are positively autocorrelated with previous returns, future returns are negatively correlated with lagged returns of other stocks, or the stock has a high mean compared to other stocks. For example, in a scenario where investors underreact to data specific to the portfolio but overreact to macroeconomic events, there is a likelihood that momentum exists but there is no autocorrelation between current firm stock price and previous stock price. As the results of our time series econometric models show, there is no autocorrelation as the Durbin-Watson statistics exceeding the upper limit of the Durbin-Watson critical values.

Why is this test inconclusive? Although we found that there is no autocorrelation amongst our data, it is necessary to perform more robust statistical calculations over a larger period of time and factor in other variables to test whether there is truly no autocorrelation amongst similar momentum stocks or if this finding is constrained to our data set. As an example, it is very possible that momentum stocks coincide with growing market bubbles, and as such, they may trend alongside larger macroeconomic events. Furthermore research into firm-specific momentum (examination of firm financial metrics and earnings) could show higher levels of autocorrelation as it isolates a specific factor that consistently guides investor's expectations of historical and future returns. This would require expansive data sets on firm-specific performance and related macroeconomic criteria.

Purpose: In the original analysis conducted by Fama and French, they conclude that the purpose of conducting a time-series regression test is to analyze how rationally priced the assets are. In essence, in order to understand whether markets are efficient, and whether the underlying value of assets are reflected in market prices, it is necessary to study the variation in stock prices over time and how they are correlated with the underlying factors of those assets (ex. risk, size, book-to-market value). By using a time-series analysis, we are able to better measure a portfolio of high-momentum stocks over a continuous period of time and understand how the three key Fama-French factors of market, size, and book-to-market equity impact the portfolio returns.

4d. Heteroskedasticity and Multicollinearity Test

Test for Heteroskedasticity

H_o: Constant variation in data
$Chi^2 = 0.97$
Probability> $Chi^2 = 0.3241$

At the 5% level, our p value is greater than 0.05. As such, we do not reject the null hypothesis and conclude the data is homoscedastic.

Test for Multicollinearity

H_o: No multicollinearity

Variable	VIF	1/VIF
hml	1.35	0.742048
mktrf	1.22	0.817514
smb	1.11	0.898439
Mean VIF	**1.23**	

Figure 15

As the mean VIF and the VIF for each variable is less than 10, we are not able to reject the null hypothesis. Thus, there is not a problem of multicollinearity.

5. Interpretation of Results

5a. Interpretation of Regressions and Tests

In order to determine the underlying factors that contribute to abnormal returns of our constructed momentum portfolio, we performed three separate OLS regressions furthered by a time series analysis of our portfolio. In each of the models, the constant (B_0) represents the alpha, α, or the abnormal return of the portfolio above the return of the market. Overall, we observe that the Fama-French three-factor model does a better job of predicting abnormal returns when compared to the capital asset pricing model (CAPM) or two-factor model.

The first OLS regression follows the CAPM wherein abnormal returns can be explained by the equity risk premium (return of the market less the return of a risk free asset). In this regression the independent variable represents the equity risk premium and the dependent variable represents the return of the portfolio over the risk free rate. This model shows an α of 0.609 that is significant at the 1% level. Furthermore, the R squared value present in this OLS regression is approximately 0.76, which means roughly 76% of the variation in the dependent variable can be explained by the regression model. The standard error of the equity risk premium is 0.0864. Our regression of the CAPM shows that holding all else constant, a 1 unit increase in the equity risk premium contributes to a 2.384 unit increase in the returns of a portfolio.

The second OLS regression, also attempting to explain the origins of abnormal returns, builds on the CAPM. While the CAPM solely focuses on the equity risk premium as an explanatory variable, the two-factor model includes the small-minus-big (size) variable alongside the equity risk premium. Recall that SMB (small-minus-big) represents the contribution of firm size (determined by market capitalization) to abnormal returns. In Fama and French's analysis, they predicted that smaller firm sizes within a portfolio will contribute to higher returns within that portfolio. As our regression for the two-factor model shows, the α is lower at 0.587 which is still significant at the 1% level. The variables mktrf and SMB have coefficients of 2.323 and 2.080 respectively while also being significant at the 1% level. The interesting thing to note here is that the R squared value in the two-factor model is considerably higher at 89.4% (meaning that 89.4% of the variation in the dependent variable is explained by the regression model). This shows that the two-factor model helps to explain abnormal returns more significantly than the CAPM. It is also important to note that the decrease in α indicates that controlling for other risk factors such as the size distribution of firms, the true abnormal return of the portfolio is not as large as CAPM initially predicted it to be. Ultimately, the two factor model shows that, holding all else constant, for every unit increase in the equity risk premium there is a 2.323 unit increase in portfolio returns and for every unit increase in SMB or the size variable, there is a 2.080 unit increase in the portfolio return. This is well in line with the hypothesis first tested with the creation of the CAPM and Fama-French models.

The third OLS regression focuses on the three-factor model. This model, originally created by Fama and French, examines how the equity risk premium (risk variable) present in CAPM alongside a size (SMB) and market-to-book (HML) variable impact portfolio returns. The third variable, HML, as mentioned previously captures the extent to which high book-to-market value equities contribute to abnormal returns. Fama and French hypothesized that high book-to-market value stocks will outperform low book-to-market value stocks in contributing to abnormal returns or α. Similarly, our three-factor model has independent variables that are all significant at the 1% level. Interestingly, the R squared value with all three factors is considerably higher than with 1 or 2 factors. For this regression, 93% of the variation in the dependent variable is explained by the regression model. Similarly, the constant, or abnormal return, is lower at 0.548. This shows that, once again, abnormal returns are smaller when incorporating additional risk factors such as the value or HML factor. The econometric model indicates that, holding all else constant, for every unit increase in the equity risk premium there is a 2.079 unit increase in the portfolio return, for every unit increase in the SMB variable there is a 1.731 increase in the portfolio return, and finally for every unit increase in the HML variable there is a 1.060 decrease in portfolio return. There are two interesting notes here: firstly, the addition of extra independent variables decreases the significance of each individual variable in explaining the root cause of abnormal returns; secondly, while Fama and French argue that high book-to-market value stocks will outperform low book-to-market stocks, the negative coefficient of the HML factor in our regression indicates that high growth stocks (low book-to-market stocks) contribute more to our returns than high value stocks (high book-to-market stocks) do. The negative coefficient can be explained due to the fact that the time frame of our analysis is simply 250 days and value stocks contribute to portfolio gains over much longer periods of time and also because high growth stocks are often correlated with high momentum stocks.

It is well known that general data on returns of stocks are heteroskedastic. This means that the variance of the error term, especially in a time series regression, is not constant over time. However, as our regression deals exclusively with the top performing (momentum) stocks in the Russell 3000 over the time period of February 2018 to February 2019, our portfolio results were more likely to be homoskedastic. Consider the explanation of momentum given previously: stocks that perform well in time period t are expected to continue to perform well in time period t+1. Since our analysis focuses on daily returns and the stocks we picked were exclusively high momentum stocks, there is little variance in the error terms of the portfolio returns.

In regards to tests for multicollinearity, it was determined that there is no evidence of collinearity between the independent variables in the Fama-French three-factor econometric model. In other words, the selected variables are not intercorrelated, but rather independent of each other. This is significant as the original CAPM uses the equity risk premium, or excess returns of investments in equities over riskless securities, as a proxy for risk. Intuitively, this risk premium would capture all other variables and characteristics of stock portfolios such as size, ratios, etc. As the Fama-French three-factor model expands upon the CAPM to include additional metrics of size (SMB) and value (HML), it would make sense that there is some collinearity between such variables and the equity risk premium as the risk premium theoretically captures all drivers of risk, and thus return, of equities. However, our findings show that while there may be collinearity between these variables, it is far smaller than expected, and not significant within the statistical analysis. By examining the correlation analysis presented in Figure 4, it is evident that the highest correlation is between the equity risk premium and the size factor, but even this correlation is only 5.97%. Similarly, the test for multicollinearity shows that mean variance inflation factor (VIF) is 1.23 which is less than 10 allowing us to conclude there is no issue with multicollinearity. Thus, our regression results accurately capture the independent effects of the Fama-French factors on our portfolio returns.

5b. Other Considerations and Biases

The CAPM serves as a rudimentary framework for the relationship between risk and return. For this reason, it is widely accepted in academic research and practice. However, the debate for which model best expands upon or replaces the CAPM framework has become especially important after Eugene Fama and Kenneth French published their three-factor model. Many argue that, while the Fama-French model serves as a viable expansion of the CAPM, there are many alternative independent variables and methodologies that can better explain the relationship between the characteristics of stock portfolios and returns.

In regards to biases, this paper shares many similar biases as the original Fama-French model. As an example, this paper assumes that the independent variables size (SMB) and value (HML) serve as the best predictors of stock performance outside of equity risk premium. It is very possible other factors, such as profitability and investment (as described in the 2015 Fama-French five-factor model) better estimate returns as these variables may serve as better indicators in and of themselves with regards to returns, but also because there are simply more variables to capture return-related information. Additionally, our analysis utilized momentum stocks (momentum theory) as it is assumed that stocks that have performed well historically will continue to perform well relative to other stocks. This assumption may create an upward bias as the momentum effect may be exaggerating the coefficients of the three independent variables in the Fama-French regression. Until a variable to isolate for momentum is introduced into the econometric model, the current independent variables may be artificially inflated in how well they capture abnormal returns.

Lastly, within the three-factor model there is an assumption that the equity risk premium is a proxy for risk. Essentially, we assume that the returns generated by equities above riskless securities is a direct factor of the risks involved by investing in the public market. As such, it is possible that this metric produces a bias in and of itself as it may not accurately reflect the true risks of the market and instead may capture other drivers of return beyond risk itself.

Parameter	Fama-French Factor Model	Other Models
Equity Risk Premium Factor (B_1)	Argues that ERP alone does not fully predict abnormal returns but is simply one mechanism of predicting such returns. A higher equity risk premium leads to higher portfolio returns.	Sharpe (1964) argues that CAPM captures the entirety of investment risk and is an appropriate proxy in and of itself for discovering abnormal returns
		Womack et. al. (2003) explain how volatility, diversification, and systematic risk all contribute to the return of an asset, concluding that the CAPM and the Fama-French models are both valuable tools used by investors.
		In contrast, Ang et. al. (2004) claim that highly volatile risk stocks with low returns cannot be attributed to size, book-to-market, momentum, and liquidity effects. This theory contradicts that of Fama and French, which posits that sorting portfolios by idiosyncratic volatility has no effect on returns.
Size Factor (B_2)	States that small capitalization firms tend to outperform large capitalization firms due to increased risk and higher cost of capital.	Ferson and Harvey (1999) found that when adjusting for variables with time-varying parameters, the three-factor model did not explain the conditional expected returns of the portfolios.
Value Factor (B_3)	Fama and French argue that companies with higher book-to-market ratios (value stocks) tend to outperform companies with lower book-to-market ratios (growth stocks). The reasoning behind this is that companies with book values that closely align with their market values consistently perform whereas the risks of growth firms are not accounted for in typical models such as CAPM.	Lakinoshok et. al. (1994) and Haugen (1995) argue that the undervaluation of distressed stocks contributes to low valuations
		Fama and French (2015) describe a possible five-factor model to better estimate returns, adding measurements for profitability and investment strategies to their original model to create a five-factor model. They also suggested removing the value variable (HML) to create a four-factor model.
Momentum	Fama and French do not explicitly include momentum in their model analyses, however, they comment on the relationship of momentum in their future research and the implications of momentum on variables in their five-factor model, such as profitability and investment. They admit that the biggest drawback of their three-factor model is its ability to account for short-term momentum anomalies.	Clare et. al. (2015) suggested momentum should be used in conjunction with trend following or trend trading, where an investor buys as prices trend upwards and sell as prices trend downwards. By using trend following as an extension of momentum, investors are able to achieve the returns affiliated with momentum portfolios, but with reduced volatility and drawdowns.

Figure 16

5c. Future Research

Within the context of this paper, future research should focus on more extensive analyses of variables which impact the returns of public equities. For this project, we sought to confirm the findings of the Fama-French model and thus looked only at the three variables used in their analysis. Research since this Fama and French posted their paper, however, have proposed many robust alternative models which capture these drivers of return.

Furthermore, while there has been thorough research and data related to the performance of stock portfolios and the predominant drivers of return, a bottom-up approach that thoroughly dissects such drivers of return could prove more useful than an otherwise systematic analysis of stock portfolios. In other words, while Fama and French built a sufficient model that expanded upon the fundamental relationship between risk and return, it may be more useful to evaluate risk by clustering firms with similar characteristics and determining the unique variables which generate returns in those categories. To illustrate this, variables such as risk, size and value in the Fama-French model are used to distinguish drivers of return across wide range of companies with different characteristics. It may prove useful to isolate companies which share similar characteristics and determine the factors which drive returns within those specific categories.

6. Conclusion

In this paper, we set out to explore the variables that contribute to abnormal portfolio returns or α. We began by constructing a momentum portfolio that holds the top 200 momentum stocks within the Russell 3000. Afterwards, we used the capital asset pricing model, a two-factor model, and the Fama-French three-factor model to perform OLS regressions and determine the extent to which the equity risk premium, the size factor, and the value factor explain portfolio returns.

Throughout this analysis, various tests were performed to confirm the validity of the OLS regressions. Tests for heteroskedasticity and multicollinearity indicated that the aforementioned regressions did not face such issues. Furthermore, after performing a time-series regression, no autocorrelation was found among variables and the no-lag, three-factor OLS regression remained robust. Therefore, the Fama-French three-factor model proved to be a credible predictor of portfolio returns. Although there are small sources of bias that may exist, their effects were relatively negligible and could be resolved in future research through the introduction of either additional variables within the regression that help explain return or variables specific to the characteristics of the portfolio whose returns are being analyzed.

Lastly, the results of the OLS regression indicate that the three Fama-French factors explain portfolio returns more significantly and appropriately than a simple CAPM or two-factor model. This is because a single-factor or two-factor model will not include important factors that contribute to portfolio risk. By using a three-factor model, we are able to explain how certain risks within a portfolio, such as a weight for small market capitalization stocks or low book-to-market value stocks raises the riskiness of a portfolio and contributes to the potential returns of the portfolio. This significantly expands upon the CAPM which simply determines abnormal returns by analyzing the equity risk premium (or the average return of the market over a riskless asset). These results align with the original findings of Eugene Fama and Kenneth French, but this analysis contributes to existing topic literature by examining a modern-day momentum portfolio and discovering the factor contributions to its returns.

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