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THE IMPACT OF SIZE AND VALUE FACTORS WITHIN AN ASSET PRICING MODEL

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ABSTRACT

This paper aims to analyze statistical data in support of the hypothesis that the Fama French Three-factor Model (FF3FM) will better describe the risk-return relationship of a portfolio than the Capital Asset Pricing Model (CAPM). That is, if the portfolio embodies specific characteristics the Fama French Three-factor Model provides compensation for. These characteristics are related to portfolio size and value as those are the two additional factors the Fama French Three-factor Model uses to describe the risk-return relationship in comparison to the Capital Asset Pricing Model. The CAPM solely relies on the portfolio's market sensitivity to predict its return. Through the results of eight linear regressions, this paper will demonstrate that the FF3FM describes the risk-return relationship better than the CAPM for US value and small-cap heavy portfolios' weekly returns over the past three years.

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Chapter 1

Background

The Development of Asset Pricing Models

As more theories and discoveries have come to fruition in the world of finance, the ability to forecast an asset's return has been one of the most targeted goals. Different models incorporating many related theories and relationships have been a common way to attempt to determine this return or fundamental asset value. One of the most foundational set of assumptions for these models is within Harry Markowitz' modern portfolio theory (Markowitz, 1952). Most notably; portfolio selection and the mean-variance criterion. Markowitz' mean-variance criterion indicates that investors will have their own personal levels of aversion to risk, causing investors to select portfolios that maximize expected return, or the mean, for their respective levels of risk, or variance.

The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is one of the very first asset pricing models that lays the foundation for the Fama French Three-factor model (FF3FM), the model this thesis is most interested in. The CAPM will act as the benchmark for the statistical analysis of the FF3FM. The CAPM uses an asset's beta, or sensitivity to the market, risk-free rate, and excess return on the market as inputs in valuing an asset (Sharpe, 1964).

Mathematically, the CAPM can be read as the following:

$$ER_i = R_f + \beta_i(ER_m - R_f)$$

Figure 1. The Capital Asset Pricing Model Equation (Jagerson, 2018)

Where

ERi = the expected return of investment on the asset

Rf = the risk-free rate

βi = the beta of the asset

(ERm - Rf) = the market risk premium

Because the CAPM uses current market data as its benchmark, the CAPM is a substantially useful benchmark when evaluating asset pricing models.

The Fama French Three-factor Model (FF3FM)

The FF3FM builds off of the CAPM by adding two additional factors – size through its SMB factor and value through its HML factor (see Appendix A). The addition of these factors aim to better incorporate firm related characteristics largely left out of the CAPM. One of the primary goals of Fama and French in developing the FF3FM was to better identify the cross-section of U.S. common stock average returns. In a conducted study, they determined that size and book-to-market equity were two key variables in successfully explaining average stock returns for the time period of 1963-1990 across the NYSE, Amex, and NASDAQ exchanges (Fama and French, 1993). Mathematically, the FF3FM can be interpreted as the following:

Figure 2. The Fama French Three-factor Model Equation (Fama and French, 1996).

$$ER_i = r_f + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \varepsilon$$

Where

ERi = the expected return of investment on the asset

Rf = the risk-free rate

β1 = the market risk premium sensitivity to the market

(rm - rf) = the market risk premium

β2 = the SMB factor's sensitivity to the market

SMB = historic excess returns of small-cap over large-cap companies

β3 = the HML favor's sensitivity to the market

HML = historic excess returns of value over growth stocks

Ɛ = error term (CFI, 2018).

CAPM Anomalies Captured by the FF3FM

Several firm characteristics proved to have an impact on average returns, yet are left out of the CAPM entirely are referred to by Fama and French as "CAPM anomalies (Fama and French 1996)." These "CAPM anomalies" are firm related ratios like book-to-market value, book-to-equity, price-to-earnings and cash flow-to-price. Opportunely, all of these ratios hold weight in the FF3FM and are therefore compensated in the three factor model unlike the CAPM (Fama and French, 1996).

Book-to-Market Ratio Compensation in the FF3FM

As previously mentioned, the FF3FM provides compensation the CAPM lacks for a ratio known as book-to-market. The FF3FM model specifically does this through its HML factor, or 'high minus low' book-to-market equity (Fama and French 1993). The book-to-market ratio, which is the inverse of the price-to-book ratio, is a key metric used by investors to identify value (Hayes, 2019). A value stock is a security that is considered to be trading at a lower price than its fundamentals indicate it should. Investors invest in value stocks in attempt to cash in on potential market inefficiencies. On the other hand, growth stocks are generally priced higher than their fundamentals support as a result of high growth potential (Chen, 2019). Due to the FF3FM defining its HML value factor as 'high minus low,' it is expected that a value stock would have a greater HML coefficient than a stock of lesser value, or in comparison to a growth stock. In fact, some investors consider a low or negative HML value to signify a growth stock as growth is generally considered the opposite of value (Efficient Frontier, 2019).

Market Capitalization Reflected in the FF3FM

The other additional FF3FM factor, the SMB, is historic excess returns of small-cap over large-cap companies. Historically, small-cap companies have been understood to reap greater returns in comparison to large-cap companies. Over a forty year period, 1926 to 2006, small-cap stocks beat large-cap by an average annual 2.3 percentage points (CFP, Robert, 2008). With the SMB factor defined as ‘small-cap over large-cap,’ it is expected that the SMB factor would be greater for small-cap companies, and better able to describe the risk-return relationship. Like the HML, some investors use different thresholds in evaluating the SML coefficient. One rule of thumb considers a value of 0.5 or more to signify a small-cap heavy portfolio, and a value of zero or less to signify a predominately large-cap portfolio (Efficient Frontier, 2019).

Chapter 2

Methodology

Data Timeline

With the intent to explore how well the FF3FM describes the risk-return relationship recently, the data used in the following regressions are from the past three years. This includes historical data from years 2016, 2017, and 2018.

Kenneth R. French Data Library

The Kenneth R. French Data Library breaks down the FF3FM model returns both daily and weekly. The weekly returns over the past three years (2016, 2017, and 2018) were chosen for the statistical testing in this thesis providing a sufficiently large sample.

FF3FM data necessary for statistical testing, provided by the Kenneth French Data Library, include the weekly market risk premium, HML, SMB, and risk-free rate values. Per the data library website, the risk premium is calculated as *the excess return on the market, value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price data at the beginning of t, and good return data for t minus the one-month Treasury bill rate (from Ibbotson Associates)* (Kenneth R. French, 2019). To provide better context of the

FF3FM market proxy magnitude, the market capitalization for US listed firms was approximately $32.1 trillion as of 2018 (United State Market Capitalization, 2019).

FTSE Russell

As previously stated, a key motivation for the development of the FF3FM was to better identify the cross-section of U.S. common stock returns (Fama and French, 1993). FTSE Russell indexes were chosen in order to test a sample that embodies U.S. common stocks. FTSE Russell's Russell US indexes are leading US equity benchmarks. Currently, an approximation of $16 trillion is benchmarked to these indexes across leading asset owners, asset managers, investment banks, and more. (FTSE Russell, 2015).

Another reason FTSE Russell is an extremely exemplary index series to use for evaluating the FF3FM is that it breaks its indexes down by both size and value; the two factors the FF3FM adds in its asset pricing model in comparison to the CAPM (FTSE Russell, 2017). All Russell US Indexes are subsets of the Russell 3000 Index which is comprised of the 3,000 largest US stocks by market capitalization. The pool of these stocks covers 98% of market capitalization for investable US equity. The Russell 3000 is broken down by size through the Russell 1000 and the Russell 2000. The Russell 1000 captures the largest 1,000 stocks by market capitalization within the Russell 3000, and the Russell 2000 captures the remaining 2,000 smaller firms in the Russell 3000 (FTSE Russell, 2018). This is essentially a large-cap (Russell 1000) versus small-cap (Russell 2000) comparison, which is how the accuracy evaluation of the FF3FM's SMB factor (see Appendix A) will be unveiled in the statistical analysis. To better understand the magnitude of these funds, the average weighted market capitalizations of the

Russell 1000 and the Russell 2000, as of February 28, 2019, were, respectively, $196.467 billion and $2.425 billion (FTSE Russell, 2019). When compared to the approximated FF3FM market capitalization of $32.1 trillion, the Russell indexes are drastically smaller samples.

As for the FF3FM's HML factor (see Appendix A), the Russell US Indexes are further broken down into Russell Value and Russell Growth. Russell Value is determined by book-to-price ratio, also known as book-to-market. Russell Growth is determined by I/B/E/S earnings growth rate two-year forecast plus sales-per-share five-year historical shares (FTSE Russell, 2018). The accuracy of the HML factor will be evaluated based on the comparison between the Russell Value and the Russell Growth indexes.

While the Kenneth R. French Data Library has FF3FM historical data already broken down into weekly returns, the FTSE Russell indexes do not. Therefore, the FTSE Russell weekly returns were calculated with a simple return formula (see Appendix A) from the daily price data that was available.

Regression Analysis

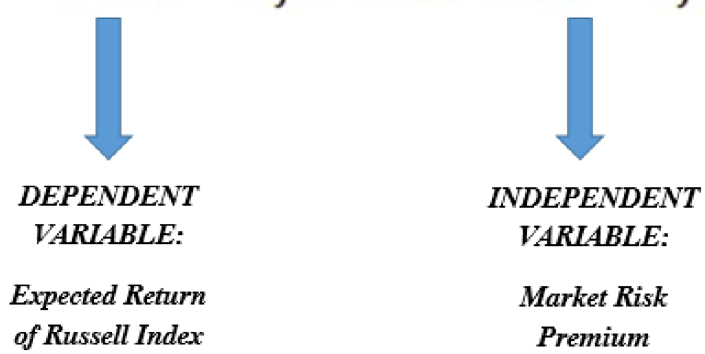
Linear regressions are used in this thesis to compare the predictability of the FF3FM and the CAPM for US weekly stock returns over the past three years (see Appendix A). IBM's SPSS software was the program specifically utilized due to its linear regression capabilities and accessibility through Penn State Libraries' software license.

A total of eight linear regressions were ran to compare the prediction accuracy of the CAPM verses the FF3FM for the weekly returns of the Russell 1000 Growth, Russell 2000 Growth, Russell 1000 Value, and Russell 2000 Value. In order to isolate a size comparison for the SMB factor, the differently sized indexes should only be compared within the specific Russell category it is in (value or growth). To solely evaluate the HML factor, only the Russell Value and Growth indexes of the same size (1000 or 2000) should be compared. However, there could be overlapping trends uncovered based on what is found in the data outputs of all of the regressions.

Referring back to the CAPM and FF3FM equations, the following figures (3 and 4) demonstrate how each model will aim to predict the risk-return relationships for the Russell indexes.

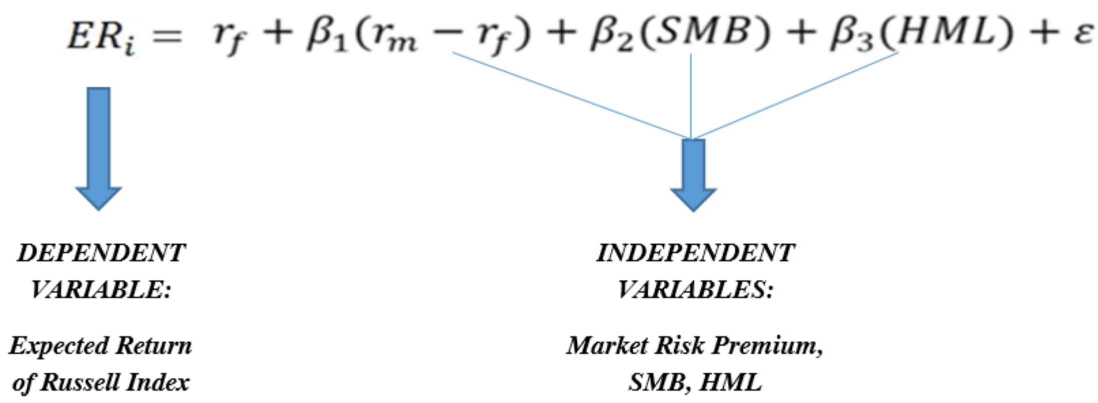
Figure 3. Russell Indexes with CAPM Regression Equation Defined

$$ER_i = R_f + \beta_i(ER_m - R_f)$$



The dependent variable for all regressions is the expected return of the respective Russell index per regression (see Appendix A). When regressing with the CAPM, the independent variable is solely the market risk premium, calculated by subtracting the risk-free rate (see Appendix A) from the market return used in the FF3FM defined above. Therefore, the most the linear regressions can tell when using the CAPM is how much the market risk factor explains the Russell returns through the value of the beta coefficient.

Figure 4. Russell Indexes with FF3FM Regression Equation Defined



The additional factors in the FF3FM, the HML and the SMB, act as independent variables along with the market risk premium. The linear regression calculates the respective coefficients for each independent variable which will then reflect how responsible each factor is for the Russell return. The linear regression output will also calculate the level of significance per factor coefficient to determine if it's a reliable explanation of the Russell return.

Chapter 3

Regression Results and Analysis

Below is a compilation of all eight linear regression results. Following the compilation are condensed tables for specific observations with detailed analyses.

Table 1. All Linear Regression Results

Linear Regression	R Square	Adj R Square	F	Mkt-Rf	*t*	*Sig*	SMB	*t*	*Sig*	HML	*t*	*Sig*
2000 Value-CAPM	0.572	0.569	205.490	0.756	*14.335*	*0.000*						
1000 Value-CAPM	0.604	0.602	235.037	0.777	*15.331*	*0.000*						
1000 Value-FF3FM	0.653	0.646	95.243	0.786	*15.768*	*0.000*	0.010	*0.196*	*0.845*	0.221	*4.609*	*0.000*
2000 Growth-CAPM	0.666	0.664	307.695	0.816	*17.541*	*0.000*						
1000 Growth-CAPM	0.674	0.672	318.061	0.821	*17.834*	*0.000*						
1000 Growth-FF3FM	0.682	0.676	108.640	0.817	*17.115*	*0.000*	-0.003	*-0.057*	*0.955*	-0.091	*-1.975*	*0.050*
2000 Value-FF3FM	0.742	0.737	145.763	0.671	*15.623*	*0.000*	0.349	*8.099*	*0.000*	0.270	*6.523*	*0.000*
2000 Growth-FF3FM	0.782	0.778	182.159	0.715	*18.119*	*0.000*	0.353	*8.918*	*0.000*	-0.019	*-0.496*	*0.621*

FF3FM Increases Predictability

Table 2. FF3FM Prediction Accuracy Increases for Large-cap Value when HML Highly Significant

Linear Regression	R Square	Adj R Square	F	Mkt-Rf	*t*	*Sig*	SMB	*t*	*Sig*	HML	*t*	*Sig*
1000 Value-CAPM	0.604	0.602	235.037	0.777	*15.331*	*0.000*						
1000 Value-FF3FM	0.653	0.646	95.243	0.786	*15.768*	*0.000*	0.010	*0.196*	*0.845*	0.221	*4.609*	*0.000*

The above table demonstrates that the adjusted R-square for the Russell 1000 Value Index is higher when regressing with the FF3FM instead of the CAPM. While the 0.044 improvement is not drastic, the high significance of the HML factor in the FF3FM infers that the

HML factor further explains the index return. This aligns with the notion that the HML will be significant and further explain expected return when value stocks are apart of the portfolio.

Table 3. FF3FM Prediction Accuracy Increases for Small-cap Value when both Factors are Significant

Linear Regression	R Square	Adj R Square	F	Mkt-Rf	*t*	*Sig*	SMB	*t*	*Sig*	HML	*t*	*Sig*
2000 Value-CAPM	0.572	0.569	205.490	0.756	*14.335*	*0.000*						
2000 Value-FF3FM	0.742	0.737	145.763	0.671	*15.623*	*0.000*	0.349	*8.099*	*0.000*	0.270	*6.523*	*0.000*

Table 3 shows the greatest adjusted R-square improvement from using the FF3FM verses the CAPM. This 0.168 improvement is for the Russell 2000 Value Index where both the SML and HML are highly significant. This continues to confirm that the HML factor is a notable addition to the model for value stocks. It also reflects that the SMB further explains the risk-return relationship for a predominantely small-cap portfolio as anticipated.

Table 4. FF3FM Highest Predictability for Small-cap Growth where Only SMB is Significant

Linear Regression	R Square	Adj R Square	F	Mkt-Rf	*t*	*Sig*	SMB	*t*	*Sig*	HML	*t*	*Sig*
2000 Growth-CAPM	0.666	0.664	307.695	0.816	*17.541*	*0.000*						
2000 Growth-FF3FM	0.782	0.778	182.159	0.715	*18.119*	*0.000*	0.353	*8.918*	*0.000*	-0.019	*-0.496*	*0.621*

The Russell 2000 Growth Index had the highest adjusted R-square value when regressed with the FF3FM. The SMB is highly significant, confirming that for both small-cap regressions, the Russel 2000 Value in Table 3 and the Russell 2000 Growth above, the SMB is a key factor addition in predicting returns for small-cap heavy portfolios.

Table 5. Approx Same Prediction Accuracy for CAPM and FF3FM for Large-cap Growth

Linear Regression	R Square	Adj R Square	F	Mkt-Rf	*t*	*Sig*	SMB	*t*	*Sig*	HML	*t*	*Sig*
1000 Growth-CAPM	0.674	0.672	318.061	0.821	*17.834*	*0.000*						
1000 Growth-FF3FM	0.682	0.676	108.640	0.817	*17.115*	*0.000*	-0.003	*-0.057*	*0.955*	-0.091	*-1.975*	*0.050*

The Russell 1000 Growth regressions results are displayed in Table 5 above. This was the Russell index in which the FF3FM regression had the least improvement, in comparison to the CAPM, of explaining the risk-return relationship. This is demonstrated by the smallest adjusted R-square difference of 0.004. Also the SMB and HML are both negative. While the SMB is not significant, the HML is. The HML value of -0.091 indicates the growth stock nature of the index as it demonstrates the index return is inversely correlated with the HML factor. The Russell 1000 Growth is the combination of large-cap and growth in which the SMB and HML were not expected to better predict the risk-return relationship in comparison to the CAPM. The minor difference of 0.004 in adjusted R-square for the different model regressions and the negative values of the additional factors support this.

Table 6. HML Highest for both Russell Value Indexes

Linear Regression	R Square	Adj R Square	F	Mkt-Rf	*t*	*Sig*	SMB	*t*	*Sig*	HML	*t*	*Sig*
1000 Growth-FF3FM	0.682	0.676	108.640	0.817	*17.115*	*0.000*	-0.003	*-0.057*	*0.955*	-0.091	*-1.975*	*0.050*
2000 Growth-FF3FM	0.782	0.778	182.159	0.715	*18.119*	*0.000*	0.353	*8.918*	*0.000*	-0.019	*-0.496*	*0.621*
1000 Value-FF3FM	0.653	0.646	95.243	0.786	*15.768*	*0.000*	0.010	*0.196*	*0.845*	0.221	*4.609*	*0.000*
2000 Value-FF3FM	0.742	0.737	145.763	0.671	*15.623*	*0.000*	0.349	*8.099*	*0.000*	0.270	*6.523*	*0.000*
2000 Value-CAPM	0.572	0.569	205.490	0.756	*14.335*	*0.000*						
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2000 Growth-CAPM	0.666	0.664	307.695	0.816	*17.541*	*0.000*						
1000 Growth-CAPM	0.674	0.672	318.061	0.821	*17.834*	*0.000*						

Analysis of Factor Significance

The above tables demonstrated that in both value funds, the Russell 2000 Value and Russell 1000 Value, the HML was a helpful factor in further explaining the risk-return relationship aside from solely the market beta like in the CAPM. Table 6 below highlights these results among all of the regression results compiled, ranked from lowest to highest HML coefficient.

Highlighted in green, the higher adjusted R square out of the two highest HML coefficients corresponded with the Russell 2000 Value Index and FF3FM regression. While the HML is slightly higher and more significant for the 2000 Value verses the 1000 Value, the high significance of the SMB for the Russell 2000 Value may be responsible for one value fund having a higher adjusted R square over the other. While the HML causes the FF3FM to be a more descriptive model than the CAPM for both Russell Value indexes, the better of the two is within the Russell 2000 Value where the SMB is also providing compensation for the small-cap quality of the portfolio.

Table 7 below ranks all of the results by lowest to highest SMB coefficient.

Table 7. SMB Highest for Russell Small-Cap Indexes

Linear Regression	R Square	Adj R Square	F	Mkt-Rf	*t*	*Sig*	SMB	*t*	*Sig*	HML	*t*	*Sig*
1000 Growth-FF3FM	0.682	0.676	108.640	0.817	*17.115*	*0.000*	-0.003	*-0.057*	*0.955*	-0.091	*-1.975*	*0.050*
1000 Value-FF3FM	0.653	0.646	95.243	0.786	*15.768*	*0.000*	0.010	*0.196*	*0.845*	0.221	*4.609*	*0.000*
2000 Value-FF3FM	0.742	0.737	145.763	0.671	*15.623*	*0.000*	0.349	*8.099*	*0.000*	0.270	*6.523*	*0.000*
2000 Growth-FF3FM	0.782	0.778	182.159	0.715	*18.119*	*0.000*	0.353	*8.918*	*0.000*	-0.019	*-0.496*	*0.621*
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2000 Growth-CAPM	0.666	0.664	307.695	0.816	*17.541*	*0.000*						
1000 Growth-CAPM	0.674	0.672	318.061	0.821	*17.834*	*0.000*						

The two highest and most significant SMB coefficients are for the two small-cap portfolios, Russell 2000 Value and Russell 2000 Growth. The impact of the SMB factor is similar to that of the HML where the added factor improved the description of the risk-return relationship for the two portfolios that embodied the characteristic the factor would compensate for. However, the crucial difference is that the higher adjusted R square for the two small-cap portfolios SMB is significant for is not the portfolio in which HML is also significant (Russell 2000 Value). The highest adjusted R square overall of 0.778 is for the Russell 2000 Growth Index and FF3FM regression. The SMB factor is most significant in this regression and the HML is arguably significant for a value close to zero representing the growth component of the index and the inability for the HML to further compensate for the risk-return relationship. It would have been expected that the most predictable and descriptive regression, if the additional FF3FM factors were relevant, was the Russell 2000 Value Index. This is due to the fact that the Russell 2000 Value Index should receive compensation from both the SMB, for being small-cap heavy, and the HML for its value characteristic. While the SMB and HML have proved to provide compensation for both components, the most successful regression was the Russell 2000 Growth Index only receiving further compensation from the SMB factor.

An observation specific to this pool of regressions is that the SMB is a more dominant factor within the FF3FM in comparison to the HML.

Beta Coefficients Ranked

Table 8. Beta Coefficient Ranked Low to High for CAPM Regressions

Linear Regression	R Square	Adj R Square	F	Mkt-Rf	*t*	*Sig*	SMB	*t*	*Sig*	HML	*t*	*Sig*
2000 Value-CAPM	0.572	0.569	205.490	0.756	*14.335*	*0.000*						
1000 Value-CAPM	0.604	0.602	235.037	0.777	*15.331*	*0.000*						
2000 Growth-CAPM	0.666	0.664	307.695	0.816	*17.541*	*0.000*						
1000 Growth-CAPM	0.674	0.672	318.061	0.821	*17.834*	*0.000*						

The above table demonstrates that when using the CAPM and solely relying on the market to describe the risk-return relationship, growth funds are more sensitive to the market. An interesting observation was made by then ranking the FF3FM results by the market coefficient, depicted in Table 9 below.

Table 9. Market Coefficient Ranked Low to High for FF3FM Results

Linear Regression	R Square	Adj R Square	F	Mkt-Rf	*t*	*Sig*	SMB	*t*	*Sig*	HML	*t*	*Sig*
2000 Value-FF3FM	0.742	0.737	145.763	0.671	*15.623*	*0.000*	0.349	*8.099*	*0.000*	0.270	*6.523*	*0.000*
2000 Growth-FF3FM	0.782	0.778	182.159	0.715	*18.119*	*0.000*	0.353	*8.918*	*0.000*	-0.019	*-0.496*	*0.621*
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1000 Growth-FF3FM	0.682	0.676	108.640	0.817	*17.115*	*0.000*	-0.003	*-0.057*	*0.955*	-0.091	*-1.975*	*0.050*

While the Russell 1000 Growth remains most sensitive to the market, the Russell 2000 Growth becomes less sensitive in comparison to the Russell 1000 Value. In other words, the two indexes that receive compensation within the FF3FM model from the SMB factors are the two least market sensitive. This is another way to consider that the SMB factor is more powerful than the HML for these regressions as the addition of the SMB further describes the risk-return relationship enough to demonstrate that the small-cap funds are less sensitive to the market than they originally appear without the SMB factor. While the HML factor does this with the Russell 1000 Value, the SMB does with greater magnitude.

Chapter 4

Conclusion

The results of the eight linear regressions confirmed many of the expected trends. The added SMB factor resulted in the FF3FM better describing the risk-return relationship than the CAPM for the two small-cap indexes: Russell 2000 Growth and Russell 2000 Value. The FF3FM also outperformed the CAPM for the two value funds, the Russell 1000 Value and Russell 2000 Value due to the addition of the HML factor in which its significance for both value indexes better explained the risk-return relationship than the CAPM. Therefore, the original hypothesis has been confirmed that when favorable size and value related characteristics are prevalent within a portfolio, specifically a small-cap and value emphasis in the case of the FF3FM, the FF3FM is a better asset pricing model than the CAPM. This was evident as the FF3FM more accurately described the risk-return relationship than the CAPM through its additional factors.

An interesting find throughout the results was that the addition of the SMB factor was more pronounced than that of the HML factor. This takeaway was first developed due to the fact that the highest adjusted R-square value was for the regression of the FF3FM and the Russell 2000 Growth. In this case, solely the SMB factor was significant as it is a small-cap growth index. If both factors were equally influential, it would be expected that the highest adjusted R-square should be from the FF3FM regression with the Russell 2000 Value, a small-cap value index where both factors were significant. It is important to note that the FF3FM regression with the Russell 2000 Value did have the highest adjusted R-square improvement in comparison to its respective CAPM regression. This demonstrates it is still ideal to have both additional FF3FM factors providing compensation. Yet it is interesting how the SMB appeared to make a bigger impact than the HML, again observed when looking at the market sensitivity rankings. When ranked by market sensitivity, the two small-cap indexes were least market sensitive among the FF3FM regressions. A potential explanation for this could be that the addition of the SMB provided significant compensation for the small-cap indexes that the market sensitivity decreased most for these indexes verses the HML addition for the value indexes in which the result was not as substantial.

Overall, the high R-square values and significant coefficients where expected demonstrate that asset pricing models can be improved and tailored to specific characteristics in order to better describe the risk-return relationship. In this case, the FF3FM was successful in doing so for the weekly returns over the past three years for US Russell Indexes separated by both size and value.

There are many asset pricing models built off of the foundation of others as the FF3FM does onto the CAPM. There is a Fama French Five-factor Model incorporating investment and profitability factors (Fama and French, 2014). There is also a model built off of the FF3FM separate from the workings of Fama and French known as the Carhart 4-factor Model (Carhart, 1997). The variety of the models and indexes, funds, portfolios, etc. with historical data available, provide many opportunities to identify models highly capable of explaining the risk-return relationship. In this case, the FF3FM was deemed more successful than solely the market at describing the risk-return relationship for US weekly returns of Russell value and small-cap indexes for the years 2016, 2017, and 2018.

Appendix A

Glossary

FF3FM Additional Factors

SMB

The SMB factor, or "small minus big," is the component of the FF3FM model that captures the difference between small-cap portfolio returns and large-cap portfolio returns. It is referred to as the mimicking return for the size factor (Fama and French 1993). Conducted stock regressions by Fama and French reflect that the SMB factor identifies shared variation among stock returns that is missed by both the market and the HML factor. This is due to the SMB's slope in stocks which is directly related to size in which it shares an inverse relationship (Fama and French 1993).

HML

The HML, "high minus low," is meant to mimic the risk factor in returns to book-to-market equity accounting for the spread between value and growth stocks. Essentially a value premium, the slope of the HML factor in stocks captures shared variation in stock returns' book-to-market equity missed by both the market and the SMB factor (Fama and French 1993).

Linear Regression Terms and Variables

Linear Regression

A linear regression is a method of predictive analysis. The equation used determines the level of accuracy an independent variable(s) is/are for predicting the outcome of its dependent variable.

R Square

As part of a linear regression output, R Square is a goodness of fit measure. Commonly listed as a percentage, R Square can take on a value between 0 and 1 (or 0 and 100%). The higher the R Square, the more predictive the independent variable(s) is/are of the dependent variable.

Adjusted R Square

Adjusted R Square is the output of R Square adjusted for the amount of predictors in the model. For the purposes of this thesis, utilizing the Adjusted R Square allows us to directly compare the results of the single and multi-factor models.

F

The output of F in a linear regression values the overall significance. It is a ratio calculated by the mean regression sum of squares over the mean error sum of squares. F can take on any value greater than or equal to 0.

t

The t statistic in a regression output has a crucial role. The value of the t statistic reflects how significant the corresponding coefficient is within a regression. In the case of this thesis, the t statistic reflects how heavily the market risk-premium, HML, and SMB coefficients affect the returns of the Russell indexes. The greater the absolute value of t, the greater evidence the coefficient is significant. A rule of thumb uses an absolute value of 2 as a threshold. However all t and p-values (see following definition) are reported in the results and evaluated with flexible relativeness.

P-value, "Signif"

The p-values in regression outputs work with t-values to determine which factors add significance to a model. The p-values in the regressions ran in this thesis are actually under the column labeled 'Signif' in all of the results tables. The lower the p-value, the more meaningful the addition of the respective predictor is. A general rule of thumb for p-values is a threshold of less than 0.05 to determine a predictor is significant.

Market Data and Calculations Used in Regressions

Formula used to Calculate Weekly Returns for FTSE Russell Indexes

All daily returns used in the following calculation were from the end of each week, matching up with the dates stated in the FF3FM data.

Weekly Return = (last day of week return - last day of previous week return)(last day of previous week return)

Russell Indexes Market Return/Risk Premium Calculation (Dependent Variable)

Testing how accurate the CAPM and the FF3FM are in predicting the weekly returns of the Russell indexes, is really seeing if the models can gauge what excess return the Russell indexes achieve in comparison to the market. Also known as the risk premium, this was calculated by subtracting the historical risk-free rate per week, which was provided in the Kenneth French Data, from the Russell weekly returns. *Russell Risk Premium = Weekly Return – Rf*

Risk-free Rate used in Kenneth R. French Data Library

The risk-free rate used in the FF3FM is a weekly Tbill return that over four weeks compounds to a 1-month Tbill rate from Ibbotson and Associates (Kenneth R. French, 2019).

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ACADEMIC VITA

KAYLA J. RHEA

EDUCATION

The Pennsylvania State University, Schreyer Honors College **University Park, PA**
Smeal College of Business | Bachelor of Science in Finance *Class of May 2019*
Minor: Supply Chain Information Sciences and Technology
Awards: Schreyer Academic Excellence Scholarship, 2019 CFA Level 1 Exam Scholarship

PROFESSIONAL EXPERIENCE

J.P. Morgan Asset Management **New York, NY**
Summer Analyst (Incoming Summer 2019 Full-Time) *May 2018-Aug 2018*

- Developed strong understanding of investment structures, fund types, and portfolio arrangements for institutional clients
- Presented the bank's market outlook to a valued client and assisted with client meeting preparation as needed
- Strengthened markets intellect by attending morning panels and sharing key takeaways with team members unable to attend
- Executed related knowledge through fund pitches and participation in analyst/associate leadership development meetings
- Conducted research on the competitive landscapes for specific lines of business to identify potential opportunities

Curtis Instruments, Inc. **Mount Kisco, NY**
Finance/Logistics Intern *May 2016-Aug 2016, May 2017-Aug 2017*

- Achieved annualized savings of $102,377 and identified potential annualized savings of $1,075,534 through cost analysis
- Created a generalized freight matrix between all international sites to help evaluate related fiscal gains and losses

LEADERSHIP EXPERIENCE

Schreyer Honors College Scholar Assistant Team **University Park, PA**
Admissions Member (year 1), Team Lead (year 2) *Aug 2016-May 2018*

- Budgeted funds for Schreyer Honors College events to build community and collaboration among 2,000+ students and staff
- Assisted Schreyer Honors College admissions staff with student interviews, accepted student days, and diversity initiatives

Schreyer Honors College Career Development Program **University Park, PA**
Co-Chair *Aug 2017-Present*

- Organized monthly meetings on various career building topics like navigating career fairs, resume tips, and personal branding
- Aligned underclassmen with upperclassmen mentors that share similar career aspirations in order to provide key guidance

Beta Gamma Sigma, International Business Honors Society **University Park, PA**
Inductee *Apr 2018-Present*

- Awarded membership into professional business society for having an academic standing within the top 7% of my class

Scholars Helping Scholars **University Park, PA**
President *Sep 2015-May 2017*

- Alleviated stress of Schreyer Honors College students by providing assistance through personalized mentorship program

RELEVANT INVOLVEMENT

Smeal Ethics Case Competition **University Park, PA**
Finalist, 2nd Place *Spring 2017*

- Paired up with peers to construct an innovative outline on how to fulfill ethical obligations within the pharmaceutical industry

Smeal Business Core Office **University Park, PA**
Exam Proctor *Aug 2018-Present*

- Administered business course exams ensuring students have a proper test taking environment and uphold the Smeal Honor Code

Wall Street Boot Camp 1 & 2 **University Park, PA**
Participant *Aug 2016-Dec 2017*

- Selected for 1 of 40 spots out of 400 applicants for semester long professional development program
- Acquired and sharpened skills necessary for a career on Wall Street through training sessions with professionals in investment banking/capital markets, sales & trading/securities, private wealth management, asset management, and equity research

ACTIVITIES

Penn State Ski Team **University Park, PA**
Team Competitor *Nov 2015-May 2016*

- Competed in Slalom and Giant Slalom races during season at course locations throughout the Northeastern region

Penn State Dance MaraTHON **University Park, PA**
Opperations Committee Member *Sep 2015-Feb 2019*

- Organized and initiated logistics of set up, performance, and tear down for THON weekend to raise funds for pediatric cancer