

EVALUATING COMPLEXITY AND MACROECONOMIC VARIABLES IN
MULTIFACTOR MODELS

by

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MULTIFACTOR MODELS

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ABSTRACT

The purpose of this paper is to identify the benefits of using multifactor models compared to the uni-factor CAPM equation. The paper then examines the explanatory power of common variables in multifactor explanations for expected returns and categorizes these variables into macroeconomic factors and firm-specific factors. This examination will help identify what macroeconomic factors play a substantial role in expected returns and whether the model benefits more by including firm-specific factors compared to macroeconomic factors.

INTRODUCTION

The expected returns of an investment greatly impact the willingness of investors to trade an asset. Expected Returns allows investors to properly gauge potential profits and risks associated with an investment. An accurate calculation of expected return is therefore essential in making an informed investment decision. Expected returns also play a significant role in corporate finance where they are used to calculate the cost of equity. Many times, this plays a substantial role in deciding the capital structure of a firm and effects the firms calculated weighted average cost of capital. Weighted average cost of capital is used as a discount factor for firms to evaluate potential projects and valuations. Because of this, an accurate calculation for expected returns is essential to making an informed decision.

Considering the importance of expected returns, many techniques have been developed for this purpose. This paper focuses on the comparison of two common techniques: uni-factor, and multifactor expected return models. To do this, the Capital Asset Pricing Model (CAPM) and a variation of this model using multiple variables in the CAPM equation is used. CAPM finds the value of the firm by identifying how the stock moves compared to the entirety of the market and adds the risk-free rate of investment. This can be seen below:

Expected Return = Risk-Free Rate + Individual stock movement compare to the market X
(movement of the market – Risk-Free Rate)

$$(E[R] = r_f + \beta(r_m - r_f))$$

Intuitively, the equation identifies a firm specific factor (its movement compared to the market) and uses this factor to evaluate the expected return for an investment. This logic can be expanded to be made applicable to equations that identify more than one factor. Including multiple factors that differentiate the financial asset should increase the accuracy of the expected return calculation as long as these factors are not already incorporated in the initial movement compared to the market. Fama-French developed a variation of the CAPM equation including two other premiums or factors (Small minus Big, and High minus Low). Small minus Big includes the firm's relative size compared to the rest of the market and High minus Low includes the firm's book to market ratio. The equation for the Fama-French Three Factor Model can be seen below:

$$E[R] = r_f + \beta_1(r_m - r_f) + \beta_2(\text{SMB}) + \beta_3(\text{HML})$$

Both of these factors work to differentiate the firm from the rest of the market as they are unique to the firm specifically and not the overall market, but the advantage of using a multifactor model must first be justified because the multiplicity of factors adds complexity to the model.

Complexity within a model may allow a model to better fit data. Conceptually, taking previous data of expected and actual returns and comparing it to the returns predicted by a CAPM equation may result in discrepancies which can be smoothed by adding additional factors will allow the model to better fit the resulting expected return. However, incorporating more features in a model to describe previously found results does not increase the predictive capabilities of a model. This is because models that incorporate more features are more likely to follow random variation instead of the underlying relationship of expected returns. Since this variation is random, holding these variables constant and projecting results can make a model less accurate in its predictability functions because it adds noise to the underlying relationship of

the asset and its expected returns. However, if there is a factor that consistently and significantly impacts the expected return of a stock, or group of stocks in a specific sector, incorporating it in an expected return calculation would be greatly beneficial.

Moreover, a multifactor model only adds benefits when it considers a factor that is not already included in a uni-factor calculation. The effectiveness of a multifactor model which includes factors that are already captured in an asset's market beta (how the asset moves in comparison with the overall market) must be questioned. If a macroeconomic factor is incorporated in the relationship of a stock's movement with the market, then its incorporation in a multifactor calculation would be moot. Its inclusion would be senseless as it adds complexity and risk of double counting without the benefits of increasing the model's explanatory power or predictive capabilities. In fact, its inclusion can make a model less accurate in producing expected returns going forward as it can distort the underlying relationship of the stock and the market.

To test these initial hypotheses, I will focus on adding macroeconomic factors into a CAPM equation. Macroeconomic factors, as described earlier, are factors that affect all stocks in the market. These factors may affect stocks to a different degree (different sensitivity). However, I presume that the differentiation in sensitivity is already incorporated in the stock's market beta. Therefore, the inclusion of macroeconomic factors in a CAPM equation should not increase the explanatory power of expected returns and may even decrease its accuracy. I will also look to how the inclusion of firm-specific factors affects a model's predictive capabilities.

Splitting potential factors that affect expected returns is a method of trying to identify common characteristics of significant factors in expected returns. If the results of the study suggest macroeconomic factors are not significant in a multifactor model, then more studies can

be conducted narrowing the range of potential factors excluding macroeconomic factors.

Creating categories for potentially relevant factors in expected return equations creates guidance in deciding what factors test for significance.

Empirical evidence suggests that there are factors that influence a stock's expected return other than the market beta. The uni-factor CAPM equation identifies the market beta as the only relevant factor for expected returns which suggests there is benefits to looking into other potential influences. If more statistically significant factors can be identified, it would be relevant to investor decisions and all firms as this equation effects a wide variety of financial decisions.

The study finds that adding macroeconomic factors to the CAPM has no significance on the model. Macroeconomic factors do not play a significant role in expected return equations. However, the study also finds previous month returns do not play a role in expected return equations. This suggests that other classifications of potentially significant factors may be beneficial. Changing the perspective on how to identify significant factors gives guidance to other possible commonalities of significant factors. More studies are required to identify these commonalities, but this study gives direction to potentially relevant commonalities and confirms that macroeconomic factors do not play a significant role in an expected return calculation.

LITERARY REVIEW

In distinguishing if multifactor models better explain expected returns, the method in which one reviews historical data must be observed and accounted for. Complexity within models increase the explanatory power when looking at historical data but is subject to overfitting and following random variation of returns. The underlying relationship of a model

can be distorted by adding complexity. Because of this, simpler models and hypothesis are generally preferred. However, if a multifactor model can identify a variable that has consistent explanatory power over an asset's expected returns, it is beneficial to include it within an expected return equation. In examining the explanatory effect of multifactor models compared to the capital asset pricing model, the Fama-French Three Factor Model is commonly used. This model is comparable to the Capital Asset Pricing Model but adds premiums for larger firms and the ratio of the firm's book-to-market value. Adding both these factors work to further distinguish variables to which the stock is exposed, and which may affect the expected return of the stock. These added variables are specific characteristics of the firm compared to the rest of the market rather than macroeconomic factors that affect the market as a whole.

Archeampong, Price and Swanzy (2016) examined the explanatory power of using a multifactor model compared to the capital asset pricing model conducting a study on the Ghana Stock Exchange. Empirical data from the study found that a multivariable model can better explain the expected returns of the stocks in the study. The study looks at the returns of all surviving stocks on the Ghana Stock Exchange from January 2002 through December 2011 (Archeampong 102). The study confirmed that larger firms resulted in higher returns, and concluded that other factors affect expected returns, not just the market beta which the capital asset pricing model implies.

Confirming the conclusion of the Archeampong, Price and Swanzy (2016) study, Connor, Gregory and Korajczyk (1995) theorize that if there are benefits to using a multifactor model, it must be that a multifactor model calculates a closer estimate to the assets stochastic discount factor. To test this Connor, Gregory and Korajczyk (1995) compare the capital asset pricing model to arbitrage pricing theory. Arbitrage pricing theory is another popular multifactor model

used to calculate expected returns. Connor, Gregory and Korajczyk (1995) finds that single factor models do not explain the common movements across assets which he attributes as an advantage for multifactor models (Connor 103). This conclusion is reached by comparing the models through a time series test, but he recognizes the added difficulty in comparison since the arbitrage pricing theory and the capital asset pricing model are not nested models (Connor 124). In determining the number of factors that offer significance in a multifactor model, Connor, Gregory and Korajczyk (1995) could not identify a consistent number. They looked at 42 groups of 30 different stocks and found that some groups were influenced significantly by few factors while others were influenced by many factors (Connor 127). There is no consensus on how many factors to use in a multifactor model due to this variability among assets.

Mackinlay, Cray (1994) in his study, question the effectiveness of both the capital asset pricing model and multifactor models. His study identifies deviations in expected returns arising from non-risk sources. By non-risk sources, Mackinlay, Cray (1994) refers to market frictions, irregularities, or situations when a calculation for a maximum Sharpe ratio is not useful (Mackinlay). He concedes that the Fama-French three factor model does a better job than the capital asset pricing model in explaining expected returns. Again, this confirms that there are factors outside of an asset's market beta that influence expected returns (Mackinlay). The study could have created progress in terms of how one thinks of expected return calculation accuracy or it could have obtained its findings through within-sample fit or data snooping. Because of this, Mackinlay, Cray (1994) thinks that one should look to other methods of calculation of expected returns instead of multifactor models or the capital asset pricing model (Mackinlay). This would suggest that a multifactor model would not entirely explain deviations from the capital asset pricing model. While this may be true, these models outperform alternative explanations. His

identification of multiple factors affecting stock prices and the superiority of multifactor models over the capital asset pricing model suggest that one can increase the effectiveness of the model if one is able to identify relevant factors with explanatory power. However, the number of factors that are significant is unknown and vary depending on the asset.

Groenewold, Nicolaas and Fraser (1997) also find a significant advantage in using multifactor models comparing the capital asset pricing model and arbitrage pricing theory. They point to the capital asset pricing model's necessary but unrealistic assumptions and empirical flaws. These flaws consist of underestimating the market risk premium and overestimating the risk-free rate typically (Groenewold 1367). Groenewold, Nicolaas and Fraser (1997) assert that while these are faults in the capital asset pricing model, a multifactor model has not replaced the use of the capital asset pricing model due to multifactor model's inability to clarify relevant factors or the number of factors relevant (Groenewold 1367).

The empirical and conceptual evidence resulting from this literature suggests that there is an advantage of using multiple factors in models in calculating expected returns. This advantage, however, is dependent on one's ability to identify factors that are significant to the assets returns. Looking at the relationship between common factors with high explanatory power is beneficial because if one is found, it can further knowledge on how assets interact with different variables and provide guidance in looking for factors which are relevant to an asset's expected return.

In attempting to identify similarity in relevant factors to be added to a multifactor model, it is important to recognize characteristics of these factors. Splitting potential factors into two categories, macroeconomic and firm-specific factors, can provide insight to what is being added by additional factors and what is already incorporated in the market beta in the uni-factor capital asset pricing model. For this purpose, firm-specific factors will be described as characteristics of

a single security while macroeconomic factors are factors to which all securities are exposed to. For example, a factor such as a big minus small premium would be classified as a firm-specific factor as it serves to evaluate the firm relative to the firm's comparative size to the overall market. A variable classified as a macroeconomic factor would be inflation as it effects all firms and inflation itself does not compare a firm characteristic to the overall market in its own right.

Looking into relationships between factors, Bilson, Christopher, Brailsford, and Hooper (2001) compare local and macroeconomic global variables in expected returns in global emerging markets. These consisted of six Latin American markets, eight Asian markets, three European markets, and two African Markets. Data was collected through a sample period from January 1985 through December 1997 (Bilson). The study finds that the exchange rate variable was the most influential macroeconomic factor with twelve of the tested markets being significantly related. However, the remaining macroeconomic factors all performed poorly. These factors included money supply, good prices, and real activity. The money supply variable was significant in six markets, while the other two variables were only significant in two each (Bilson). The paper then tests firm-specific factors in these emerging markets, finding these variables have much more significance. The highest significance firm-specific factors were price-to-earnings and dividend yield. The study concludes that firm-specific factors are the most relevant factors to incorporate in a multifactor equation (Bilson). The study finds that factors that are specific to the firm incorporated into a multifactor model increases the explanatory power of the model, but macroeconomic factors do not significantly affect the model's accuracy with the exception of exchange rates when comparing international markets.

Testing for the explanatory significance of macroeconomic factors in multifactor markets, Al-Zubi, Khaled and Salameh (2007) conducted a study looking at the Jordan stock

market. This study focused on the industrial sector and used data collected in monthly intervals from July 1997 through December 2003. The variables tested in this study consisted of industrial production, expected inflation, unanticipated inflation, and term structure (Al-Zubi 106). The result of the study was that the model had negative explanatory power of expected returns indicating that this was a poorly fitting model. Industrial production and term structure had no significance on the study. However, the study found that inflation was significant to stock returns as well as unanticipated inflation. This suggest stock can be used to hedge inflation (Al-Zubi 118). Again, this study finds a lack of success in incorporating macroeconomic factors within a multifactor model to better fit historical data or explain expected returns.

Testing for the effect of incorporating firm-specific factors, Baetge, Jorg and Kirsch (2010) find contradicting evidence for including a size premium in an expected return calculation. The study looks at returns on the German stock market between 1995 and 2008 (Baetge 2). Conceptually Baetge argues that the capital asset pricing model is a closed model derived by the underlying assumption that investors optimally weight their portfolios to maximize returns and this cannot be modified ex post (Baetge 3). Baetge, Jorg and Kirsch (2010) concludes from his stock that size premiums are found more in large firms compared to small firms, but the statistical significance of the premiums depend on the proxy of the market (Baetge 10).

METHODOLOGY

To test the effects of macroeconomic factors in multifactor expected return calculations, a linear regression should be run comparing individual companies or indexes to the overall market.

The result of this regression will show how the dependent variable (individual stock) is influenced by the results of the independent variable (the market). This will describe the relationship in movement between the stock price and the movement in the factors used. The above description of using the overall market as the independent variable is an example of a uni-factor model. However, multiple factors can be added to describe the relationship between a stock and the multiple factors to which the stock is regressed. A model with multiple factors can be beneficial if the relationship between the variables is strengthened by adding additional factors.

This study analyzes the explanatory factor of using a multifactor model compared to a uni-factor model. The effect of multiple factors will be evaluated based on whether adding additional factors to a regression significantly increases the independent variable explanatory power of a stock price movement and if each independent factor is significant in the movement of the stock price. Each stock or index will have two models associated with it. One model will be a regression of the stock and the overall market and the other model will be a regression of the stock, the overall market, and multiple macroeconomic factors. The difference between the models will then only be the effect of adding macroeconomic factors to the model's regression. The resulting difference will then be judged significant or insignificant by the variation of the two models individual factor betas, P-Value, T-Statistic, and adjusted R-square values.

Beta in a regression refers to the percent change in the outcomes variable for every one percent change in the predicting variable (Regression). In a uni-factor model, this refers to the change in stock price for every one percent change in the overall market. Applied to a multiple factor model, it is the change in the stock price compared to a one percent change in the overall market or a macroeconomic factor (such as unemployment, treasury rate, oil price, inflation etc.).

This describes how the stock moves with the predicting variable over the number of observations regressed.

Beta, however, must first be determined to be a significant factor in the prediction of the outcome variable. This means that beta must be significantly different than zero. To determine this, the regression's t-Statistic is assessed. A t-Test determines if a beta coefficient is significantly different than zero, and therefore, significant in the model. If the beta coefficient is not significantly different than zero, the predictive variable does not predict the outcome variable (Regression). This becomes very important in testing multifactor models, as it is important to assess whether a new factor is significant in its predictive capability of an outcome variable. If new factors are not significant, then a multifactor model is not necessary for an expected return equation as it does not significantly impact the regression or its predictive capabilities.

Similarly, the significance of multiple variables will be evaluated based on their individual P-Values. P-Values tests the null hypothesis that the coefficient equal zero. This would mean that the coefficient has no effect (Frost). Historically, a P-Value of less than .05 indicates that the null hypothesis should be rejected and means the coefficient is meaningful in the regression. This is because changes in the predictors' value are related in the changes of the outcome variable (Frost).

Lastly, R squared is used to test the significance of factors in a regression. Also considered the coefficient of determination, R squared is interpreted as the percent of variance in the outcome variable that is explained by the predictor variables (Regression). R-squared provides a goodness-of-fit measurement to linear regressions as it demonstrates the percent of variance that the independent variables can explain (Frost). Comparing the collective R-Square

value of a multiple regression to a R-Square of a uni-factor regression will demonstrate the added or subtracted ability of a multifactor model to explain the percent of variance of a stock. This comparison will be useful in determining if a combination of the macroeconomic factors provides an explanatory advantage over uni-factor methods. R-Square will always stay the same or increase with an introduction of another predictor variable based on how it is calculated mathematically (Adjusted R-Square). To account for this, Adjusted R-Square should be used to compare the effect of additional predictive variables on the model (Adjusted R-Square).

Adjusted R-square will address the explanatory power of the independent variables over the outcome variable. Therefore, the adjusted R-square is necessary to evaluate when speaking to complexity of a model. As discussed above, adding complexity to a model can make the outcome distorted from the true underlying relationship as it can follow random variation. Adjusted R-square is thought of as a goodness-of-fit measurement so in the case of multivariable regressions one would suspect adjusted R-square to be higher if the added factors are significant to the regression. An increase in adjusted R-square represents that the model does a better job of explaining the outcome variable. However, this does not necessarily mean it increases its ability to predict future returns.

STUDY

To the compare the effect of multivariable regressions on expected return equations, I conducted regressions on multiple stocks in different market sectors and indexes. Including different market sectors should ensure the accuracy of calculations as some sectors are more exposed to certain macroeconomic variables than others. For example, I would suspect that a

company such as Chevron is more exposed to the percent change in oil prices than a company in the financial services sector. Macroeconomic factors tested include inflation, one-year treasury maturity rates, twenty-year treasury maturity rates, unemployment rates, adjusted monetary base percent change, and oil price percent changes. To represent the overall market, I regressed the individual stocks and indexes to the S&P 500. I then regressed the stocks to the S&P 500 and the macroeconomic factors indicated to see the effect on the regressions adjusted R-square. Beta, T-Stat, and P-value was analyzed individually to see if the presence of the factor in the regression had a significant impact on the resulting relationship. Data used in the study consisted of monthly returns including 120 observations. Macroeconomic variables such as unemployment, short, and long-term maturity rates were pulled from the Federal Reserve Bank economic research website. Historical oil prices were pulled from IndexMundi and input into Excel where a regression could be run. Percent change on a monthly basis was calculated for each macroeconomic variable to keep the data consistent with the stock and index data. For individual stock and indexes, monthly adjusted close prices were used to calculate monthly percent change. The results of this are displayed in the tables below:

Macroeconomic Regression Tables

^DJJ				
	Beta	T-Stat	P-Value	Adj. R-Square Multifactor
S&P 500	0.90	35.43	0.0%	0.931
Inflation Percent Change	-0.87	-2.52	1.3%	
1-Year Treasury Maturity Rate Percent Change	0.00	0.17	86.3%	
20-Year Treasury Maturity Rate Percent Change	0.00	-0.12	90.8%	Adj. R-Square Unifactor
Unemployment Rate Percent Change	0.00	-0.08	93.8%	0.929
Adjusted Monetary Base Percent Change	0.03	0.69	49.0%	
Oil Price Percent Change	0.04	2.49	1.4%	

CVX				
	Beta	T-Stat	P-Value	R-Square Multifactor
S&P 500	0.98	8.55	0.0%	0.472
Inflation Percent Change	-0.58	-0.38	70.8%	
1-Year Treasury Maturity Rate Percent Change	0.03	0.91	36.7%	
20-Year Treasury Maturity Rate Percent Change	-0.11	-1.44	15.2%	Adj. R-Square Unifactor
Unemployment Rate Percent Change	-0.06	-0.37	71.4%	0.464
Adjusted Monetary Base Percent Change	0.15	0.83	40.7%	
Oil Price Percent Change	0.18	2.59	1.1%	

APPL				
	Beta	T-Stat	P-Value	R-Square Multifactor
S&P 500	0.95	5.30	0.0%	0.244
Inflation Percent Change	-1.17	-0.48	63.1%	
1-Year Treasury Maturity Rate Percent Change	0.03	0.56	57.3%	
20-Year Treasury Maturity Rate Percent Change	-0.10	-0.83	41.0%	Adj. R-Square Unifactor
Unemployment Rate Percent Change	0.08	0.31	75.9%	0.254
Adjusted Monetary Base Percent Change	0.01	0.03	97.5%	
Oil Price Percent Change	0.21	1.94	5.5%	

AXP				
	Beta	T-Stat	P-Value	R-Square Multifactor
S&P 500	1.04	8.33	0.0%	0.449
Inflation Percent Change	0.73	0.43	66.8%	
1-Year Treasury Maturity Rate Percent Change	0.05	1.48	14.2%	
20-Year Treasury Maturity Rate Percent Change	-0.01	-0.15	88.0%	Adj. R-Square Unifactor
Unemployment Rate Percent Change	0.07	0.37	71.3%	0.449
Adjusted Monetary Base Percent Change	0.17	0.89	37.3%	
Oil Price Percent Change	0.09	1.26	20.9%	

MMM				
	Beta	T-Stat	P-Value	R-Square Multifactor
S&P 500	1.13	12.35	0.0%	0.601
Inflation Percent Change	-2.18	-1.76	8.1%	
1-Year Treasury Maturity Rate Percent Change	-0.01	-0.24	81.4%	
20-Year Treasury Maturity Rate Percent Change	0.05	0.82	41.4%	Adj. R-Square Unifactor
Unemployment Rate Percent Change	0.01	0.11	91.6%	0.580
Adjusted Monetary Base Percent Change	0.25	1.81	7.3%	
Oil Price Percent Change	-0.08	-1.43	15.5%	
BA				
	Beta	T-Stat	P-Value	R-Square Multifactor
S&P 500	1.07	6.53	0.0%	0.303
Inflation Percent Change	-3.39	-1.52	13.1%	
1-Year Treasury Maturity Rate Percent Change	0.00	0.01	99.2%	
20-Year Treasury Maturity Rate Percent Change	-0.06	-0.55	58.6%	Adj. R-Square Unifactor
Unemployment Rate Percent Change	-0.07	-0.28	77.8%	0.322
Adjusted Monetary Base Percent Change	0.19	0.77	44.5%	
Oil Price Percent Change	0.11	1.11	26.8%	
^RUT				
	Beta	T-Stat	P-Value	R-Square Multifactor
S&P 500	1.07	15.86	0.0%	0.731
Inflation Percent Change	0.07	0.08	94.0%	
1-Year Treasury Maturity Rate Percent Change	0.02	1.11	27.1%	
20-Year Treasury Maturity Rate Percent Change	0.09	2.02	4.5%	Adj. R-Square Unifactor
Unemployment Rate Percent Change	-0.03	-0.28	78.1%	0.719
Adjusted Monetary Base Percent Change	0.12	1.19	23.5%	
Oil Price Percent Change	-0.05	-1.17	24.4%	
XOM				
	Beta	T-Stat	P-Value	R-Square Multifactor
S&P 500	0.88	8.83	0.0%	0.485
Inflation Percent Change	-0.58	-0.43	66.8%	
1-Year Treasury Maturity Rate Percent Change	0.01	0.41	68.2%	
20-Year Treasury Maturity Rate Percent Change	-0.06	-0.95	34.4%	Adj. R-Square Unifactor
Unemployment Rate Percent Change	-0.21	-1.50	13.8%	0.483
Adjusted Monetary Base Percent Change	0.08	0.55	58.4%	
Oil Price Percent Change	0.13	2.11	3.7%	

Firm Specific Table

APPL				
	Beta	T-Stat	P-Value	Adjusted R-Square
S&P 500	1.023	6.273	0.00%	0.245
Previous Month Percent Change	0.085	1.067	28.82%	
^DJI				
	Beta	T-Stat	P-Value	Adjusted R-Square
S&P 500	0.925	38.259	0.00%	0.928
Previous Month Percent Change	-0.001	-0.022	98.23%	
CVX				
	Beta	T-Stat	P-Value	Adjusted R-Square
S&P 500	1.05	9.85	0.00%	0.456
Previous Month Percent Change	-0.06	-0.85	39.73%	

RESULTS

Based on the empirical data of these individual stocks and indexes, the effect of adding macroeconomic factors in an expected return equation is negligible. Between all regressions the effect of the multiple factors on Adjusted R-square are very small and inconsistent. This means adding macroeconomic factors to an expected return regression inconsistently affects the explanatory power of the regression. This makes sense as specific stocks in different industries have higher exposure to specific macroeconomic factors compared to others that are not as closely related. However, adding macroeconomic factors to a regression including a market beta can also decrease the explanatory power of the regression. The two stocks that experienced a decrease with macroeconomic factors were Boeing and Apple. These two stocks also had the smallest adjusted R-square values in both the multifactor model and uni-factor model. This suggests that a uni-factor or multifactor regression with the S&P 500 does not explain the movement of either Apple or Boeing very well. This suggests that the macroeconomic factors used in the study are related to or encapsulated by the market beta of a stock. A macroeconomic factor such as inflation affects the entire market (in this case the S&P 500) and the individual stock. Because of this, even if a stock is closely related to a specific macroeconomic factor, there

is very minimal benefit from including that macroeconomic factor in a regression with the stock and the market.

Of the six multivariable regressions there are only four instances of macroeconomic factors being meaningful in the regression in terms of P-Value. Two of these instances are the percent change in oil price regressed with an energy company. Chevron and Exxon both had P-Values of oil price percent change under .05 while the rest of the factors were not statistically significant. The positive betas for oil price percent changes for both Chevron and Exxon suggest that when oil prices increase so does the price of these companies.

Other instances of significant macroeconomic factors include long-term maturity rates regressed with the Russell 2000, and the change of inflation regressed with the Dow Jones Industrial Average. Referring to the significance of long-term maturity rates on the Russell 2000, the significance of this factor is related to investor decisions to invest in stock or other financial assets. Russell 2000 is an index comprised of 2000 stocks which can serve as a proxy for the market. The positive beta in this relationship suggests as long term maturity rates increase, the Russell 2000 (a market proxy) increases as well.

In cases where there were statistical significances in incorporating macroeconomic factors, the difference in adjusted R-square was minimal. Similarly, the betas of these statistically significant factors were in the range of .05 to .13. For every one percent change in the macroeconomic factor, the company or index would move less than .13 percent. While the difference is meaningful, in practice this difference is negligible. Most expected return calculations use forward looking betas based on assumptions which are not perfect. A beta of less than .13 for a macroeconomic factor would make it necessary to forecast values for the extra variable which can be misleading if not done correctly. Calculations for expected return are

inherently inaccurate but are useful for an estimation to provide guidance in investment decisions. Identifying factors responsible for large variations between a stock's return and its expected return are beneficial, but factors that create minimal differences are less important to incorporate. Therefore, the added benefits of including these factors do not justify the added assumptions and calculations needed to include them.

To test the effects of firm-specific factors included in a multifactor calculation, a regression between an individual stock, the market, and the stock's previous month percent change was run. The previous month percent change is specific to the firm as it does not affect the overall market and it is a value that is uniquely related to an individual security. A factor such as previous returns may uncover a relationship between the stock's movement and momentum of the stock. In other words, if a company had a noticeable percent change over the previous month that trend may influence the return on the current month. Testing this, the Dow Jones Industrial Average, Apple, and Chevron was used. In each case, the previous month's returns did not play a significant factor in the regression. The results for Apple can be seen below:

The P-value and lack of change in the adjusted R-square value indicate that the factor is not significant to the regression. This firm-specific factor was not a relevant factor in expected returns, however, others such as factors included in the Fama-French model prove to be relevant. The study looking at previous month returns does not conclude that all firm-specific factors are not relevant, but it demonstrates that this specific factor is not relevant. However, if there are instances where some firm-specific factors are relevant, and some are not it suggests that the classification of firm-specific factors may not be the key differentiation for significance. The inconsistency of significance within the categories of macroeconomic and firm-specific may

suggest that the classifications of macroeconomic factors and firm-specific factor are not the correct classifications of potentially significant factors. Although no relationship was found, the study works to develop an understanding of the relationship of relevant factors. Finding no relationship between relevant factors and the factors ability to differentiate a firm, the study suggests that there are different commonalities in factors that are relevant in the equation.

DISCUSSION AND IMPLICATIONS

The results from this study suggest that relevant factors in calculating expected return equations do not include macroeconomic variables. The lack of significance (demonstrated by the P-Value in the factors tested) suggest that in trying to identify relevant factors, one should look at other potential factor classifications. In looking at the effect of a firm-specific factor such as the previous months return, there was no significance as well. The study suggests categorizing relevant factors in terms of their effects on the entire market or specific stock may not be the best approach. There are other ways to conceptualize potential factors which may uncover similarities in these factors.

The Fama-French model, based on empirical data of previous studies, demonstrates that significant factors are present outside of a firm's market beta. While initially hypothesizing that these factors were relevant to expected returns by differentiating the firm from the market (much like a market beta), their relevance in expected returns can be signaling a different relationship.

Analyzing the Small Minus Big premium, it is a metric that reflects the outperformance of small-cap companies over large-cap companies (Fama-French Three-Factor Model). This factor does differentiate the firm from the rest of the market, but it also is used to classify a firm into a specific category of the market i.e. small-cap firm. Similarly, the Fama-French High

Minus Low factor, differentiates the firm, but also classifies it as a value firm based on the firm's book-to-market ratio (Corporate Finance Institute). In conducting the study, the focus of classifying factors was on their ability to differentiate a stock from the overall market. However, it is possible that factors are significant based on their ability to categorize stocks into different stock classifications such as growth, small cap, etc.

Stock classifications consist of many different categories including income stocks, penny stocks, speculative stocks, growth stocks, cyclical stocks, defensive stocks, and value stocks (Treadwell). If the inclusion of Big Minus Small and High Minus Low factors in the Fama-French model are relevant due to their ability to classify a stock into a specific category, all these stock classifications can be relevant factors in expected return equations. This also assumes these factors have different risk and returns related to their classifications. However, it is seen in the Fama-French model that classifying stock as a value stock and a small-cap stock does create a more accurate expected return calculation. This suggests that different classifications of stock have different risks and returns associated with them and incorporating betas for these classifications may be useful. Growth and value classifications identify a specific segment of the market that consistently perform different relative to the rest of the market. The consistency of performance within a stock classification is promising when theorizing of the significance of adding a beta according to the company's classification. For example, small-cap stocks consistently outperform large-cap stocks and this consistency may be the relevant relationship between significant factors of expected returns.

The relevance of the study provides guidance to which factors are significant in an expected return equation. While the results of the study show insignificance of macroeconomic factors in multifactor calculations, it led to a different perspective as to which factors are

significant. This can be important to all investment decisions if the relationship between the expected return calculations and the classification of the stock are significant. To test this new hypothesis, a study of the change in expected returns of different classifications should be evaluated. If there are statistical differences in expected returns of different stock classifications (other than only value and small cap), then a multifactor model incorporating betas for all stock classifications should be evaluated. This could increase the accuracy of the calculation in the same way the incorporation of High Minus Low and Small Minus Big effects the equation.

The findings from the study confirm the initial hypothesis that macroeconomic variables do not significantly affect a multifactor expected return equation. The study also finds that firm-specific factors do not consistently effect the equation as well. This was shown when adding the firm's previous month returns did not prove to be significant. This result is surprising as the ability of a factor to differentiate a firm from the market was suspected to be the characteristic of a relevant factor. This suggests the possibility that classifying factors by their ability to differentiate a firm is not the correct way to classify potential factors. Instead, a possible relationship of potentially relevant factors can be the factors ability to categorize a stock within a stock classification.

CONCLUSION

This paper serves to question the relevance and effect of adding multiple variables in a capital asset pricing model equation. Initially philosophizing that including multiple factors would not affect the equation significantly, former studies and literature show a slight benefit of using the Fama-French model. However, this model is unable to identify relevant factors or the number of factors one should use in the regression. Splitting potential factors into macroeconomic factors and firm-specific factors would be useful to suggest which (if any

factors) would be consistently relevant in the equation. Assuming that macroeconomic factors are relevant in the movement of the overall market and individual stocks, the effect of adding macroeconomic factors would be insignificant to the calculation. This was confirmed in the majority of cases. In cases where a stock is over exposed to a specific macroeconomic factor, such as Exxon or Chevron and oil prices, the factor did become significant. In these cases, the relationship between the stock and factor is intuitive and its overall effect on the regression was minimal. Looking at firm-specific factors, previous month returns did not play a relevant factor in the regression. In terms of complexity and distorting an underlying relationship by following random variation, this study showed no evidence of these concerns based on the adjusted R-square, and P-Values.

The overall effect of this study suggests that the classification of macroeconomic variables and firm-specific variables is not the most efficient way to identify relevant factors. More research is necessary to identify a relationship between relevant factors. However, the commonality of High Minus Low and Big Minus Small factors to categorize a stock, suggests that the ability to categorize a stock into one of multiple stock classifications may be the correct way to theorize potentially relevant factors. These classifications also provide more consistency in returns.

Annotated Bibliography

“Adjusted R-Squared - Overview, How It Works, Example.” *Corporate Finance Institute*

corporatefinanceinstitute.com/resources/knowledge/other/adjusted-r-squared/.

Al-Zubi, Khaled A. and Hussain Salameh. “Explaining the Stock Return Via a Macroeconomic

Multifactor Model.” *Jordan Journal of Business Administration*, vol. 3, no. 1, 2007, pp.

106-120

Archeampong, Prince and Sydney Kwesi Swanzy.” Empirical Test of Single Factor and Multi-

Factor Asset Pricing Models: Evidence from Non-Financial Firms on the Ghana Stock

Exchange.” *International Journal of Economics and Finance*, vol. 8, no. 1, 2016, pp. 99-

110.

Baetge, Jorg and Kirsch, Hans-Jurgen and Koelen, Peter and Schulz, Roland, “On the Myth of

Size Premiums in Corporate Valuation: Some Empirical Evidence from the German

Stock Market.” *Journal of Applied Research in Accounting and Finance (JARAF)*, Vol.

5, No. 1, pp. 2-15, 2010. Available at SSRN: <https://ssrn.com/abstract=1655692>

Bilson, Christopher M., Timothy J Brailsford, and Vincent J Hooper. “Selecting Macroeconomic

Variables as Explanatory Factors of Emerging Stock Market Returns.” *Pacific-Basin*

Finance Journal, vol. 9, issue 4, 2001, pp. 401-426

Connor, Gregory and Robert A. Korajczyk. “Chapter 4 The Arbitrage Pricing Theory and

Multifactor Models of Assets Returns.” *Handbooks in Operations Research and*

Management Science, vol. 9, 1995, pp. 87-147, *ScienceDirect*

“Crude Oil (Petroleum) Monthly Price - US Dollars per Barrel.” *IndexMundi*,

www.indexmundi.com/commodities/?commodity=crude-oil&months=180.

Fama, Eugene F. and Kenneth R. French. “Multifactor Explanations of Asset Pricing

Anomalies.” *The Journal of Finance*, vol. 51, issue 1, pp. 55-84

Fama, E. F.; French, K. R. (1993). “Common risk factors in the returns on stocks and bonds”.

Journal of Financial Economics. 33: 3–56.

“Fama-French Three-Factor Model – Components, Formula, & Uses.” *Corporate Finance*

Institute. January 29, 2020.

Frost, Jim. “How to Interpret R-Squared in Regression Analysis.” *Statistics by Jim*, 30 May

2019, statisticsbyjim.com/regression/interpret-r-squared-regression/.

Groenewold, Nicolaas and Patricia Fraser. “Share Prices and Macroeconomic Factors.” *Journal*

of Business Finance & Accounting, vol. 24, 1997, pp. 1367-1383

Johnson, Neil F. (2009). “Chapter 1: Two's company, three is complexity”. *Simply complexity: A*

clear guide to complexity theory. Oneworld Publications.

MacKinlay, Craig A. “Multifactor models do not explain deviations from the CAPM.” *Journal of*

Financial Economics, vol. 38, 1994, pp. 3-28

Petkova, Ralitsa. “Do the Fama-French Factors Proxy for Innovations in Predictive Variables?”

The Journal of Finance, vol. 61, no. 2, 2006

“Regression.” *Statistics Solutions*, [www.statisticssolutions.com/directory-of-statistical-analyses-](http://www.statisticssolutions.com/directory-of-statistical-analyses-regression-analysis/regression)

[regression-analysis/regression](http://www.statisticssolutions.com/directory-of-statistical-analyses-regression-analysis/regression).

Rickard, John T., and Nicolo G. Torre. "Theory of optimal transaction implementation." *Signals, Systems & Computers*, 1998. Conference Record of the Thirty-Second Asilomar Conference on. Vol. 1. IEEE, 1998.

Shanken, Jay. "Multi-Beta CAPM or Equilibrium-APT?: A Reply." *The Journal of Finance*, vol. 40, no. 4, 1985, pp. 1189–1196. *JSTOR*, www.jstor.org/stable/2328402.

Treadwell, Lauren. "7 Categories to Classify Stocks". *The Nest*.

"Unemployment Rate." *FRED*, U.S. Bureau of Labor Statistics, 3 Apr. 2020, fred.stlouisfed.org/series/UNRATE#0.

Weaver, Warren (1948). "Science and Complexity". *American Scientist*. 36 (4): 536–44.