Measuring Effectiveness of Quantitative Equity Portfolio Management Methods

The Honors Program
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ABSTRACT

In this paper, I use quantitative computer models to measure the effectiveness of Quantitative Equity Portfolio Management in predicting future stock returns using commonly accepted industry valuation factors. Industry knowledge and practices are first examined in order to determine strengths and weaknesses, as well as to build a foundation for the modeling. In order to assess the accuracy of the model and its inherent concepts, I employ up to ten years of historical data for a sample of stocks. The analysis examines the historical data to determine if there is any correlation between returns and the valuation factors. Results suggest that the price to cash flow and price to EBITDA exhibited significant predictors of future returns, while the price to earnings ratio is an insignificant predictor.

INTRODUCTION

Quantitative Equity Portfolio Management (hereafter, QEPM) models have become increasingly popular in the asset management field over the past decade. Many large institutions such as hedge funds use these strategies involving quantitative equity portfolio management as parts of their product offerings to clients. Although there is no single industry standard, there are generally accepted practices used by many firms.

In this paper, I review the QEPM methods used in the industry, and discuss their strengths and weaknesses. Second, I estimate a quantitative model that includes factors such as price/EBITDA, price/cash flow, and price to earnings to test some common industry portfolio management strategies. These factors are generally accepted across the industry to be significant factors in predicting future stock returns. The empirical results of this testing suggest that price/EBITDA and price/cash flow appear to be most effective at forecasting stock returns.

The results of this paper, however, are by no means proposed to offer a dispute-settling answer to the industry debate over the “best” factors and models. There is simply not sufficient time and resources to fully answer this question. Rather, this project aims to increase the body of knowledge on this subject by conducting a literature review, and offering some new insights on quantitative equity portfolio management theory.

The remainder of this paper is organized as follows. In the next section, I conduct a review of the relevant literature. This review of industry knowledge and practices assists in formulating a basis of comparison and testing. In the following section, I outline the modeling processes and framework. The details of the selected data and quantitative methods are discussed in this section, along with explanations as to why various processes were selected. The next section provides the empirical results of the testing and analysis. The final section offers conclusions and discusses some areas of proposed further research.

REVIEW OF LITERATURE

Previous Literature and Theory

There are numerous methods for valuing equity securities; including methods more heavily employed before the advent of quantitative equity portfolio construction and management. These theories include the arbitrage pricing theory (APT), capital asset pricing model (CAPM), and discounted cash flow (DCF). Although modern portfolio management still employs these models, they have been replaced with newer, more effective models such as quantitative equity portfolio management.

According to the quantitative equity portfolio management theory, several factors including price to earnings, price/earnings before interest, taxes, depreciation, and amortization (EBITDA), and price/cash flow are important in the fundamental factor modeling process. Price/EBITDA is the ratio of the current price to a different iteration of the firm's earnings. The price/cash flow ratio measures the security's price in relation to its generated cash flow, which is a measure of operating efficiency. The price to earnings ratio, or P/E, is illustrated as the price of the underlying stock divided by the annual earnings of the target firm. This helps determine the fair value of the firm. According to QEPM, the price of a given security can be significantly attributed to a combination of these factors. The importance of these factors, however, may vary for different stocks making it important to determine their influence on an individual basis. Thus, in order to build a useful model for each stock these factors must be measured against time in predicting historical returns in order to make the model truly significant.

In a seminal piece by Roll and Ross (1995), they argued that an asset's returns can be predicted by using the relationship between that same asset and many common risk factors. This theory predicts a relationship between the returns of a portfolio and the returns of a single asset through a linear combination of many independent macro-economic variables. Thus, the arbitrage pricing theory makes the assumption that the future price of a given asset can be based on a few factors such as the risk free rate, risk premiums of the given firm, industry, or broad based market, and macroeconomic factors (Roll 124). Although this model may seem to be fairly extensive, however, it is not a good solution for every type of security. For example, some macroeconomic or firm-specific factors might be more important than others. This model does not take optimal weights into account, and does not involve statistical regression analysis in such a manner that quantitative models do. The model is often used in conjunction with the capital asset pricing model, because it is by no means a complete, standalone pricing model since it does provide sufficient information to take into account the necessary factors and their weighted exposures to influencing the future pricing of the security at hand.

Another methodology employed in the field of financial economics is the capital asset pricing model (CAPM). This model takes into account a security's beta, or risk in relation to a particular benchmark, the risk free rate, and expected market return; or market risk premium (Black et al. 84). This simplified model does not take into account many economic and financial factors that impact the pricing of a security no do investors have the ability to influence the price of the security. Many hedge funds and other financial institutions, however, deal in large blocks of securities, and it is not uncommon for them to move the markets and respective prices. The CAPM is often used in conjunction with other pricing models such as the arbitrage pricing theory.

A more focused method is discounted cash flow valuation, or free cash flow analysis, which involves projecting a firm's financial statements into the future based on historical information. This practice is very similar to some aspects used in quantitative equity portfolio construction theory. The main theory behind this valuation model is the time value of money. When employing DCF, however, there are also many dangerous assumptions that need to be made, such as future growth rates and other difficult to predict operational and financial values. Typically, once the financial statements are forecasted, they are used to compute projected free cash flow available to investors. These figures are then discounted to reflect the time value of money, and the cost of this capital. The price estimate yielded by this method is often highly sensitive to nearly every model input. The DCF model also fails to take into account external factors such as industry trends, economic factors, and other important objects of influence.

Although the CAPM, APT, and DCF each have unique benefits and strengths, they all suffer from some pitfalls. Thus, combining all of these models is not likely to yield an extremely accurate projection. Quantitative equity portfolio construction and management aims to resolve these issues by utilizing an almost immeasurable list of factors with respective weights.

<u>Control Factors</u>

In order to limit firm specific risk and to increase statistical significance, we augment these three factors with the Fama-French three factor model. This model first developed Eugene Fama and Kenneth French (Fama and French 427), has proven to be very effective at illustrating the behavior of the stock market. The Fama-French model take into account the risk free rate (in terms of the 1 month Treasury bill), SMB (small market capitalization minus big), and HML (high price to book minus low). These factors are derived from the beliefs that small cap stocks tend to outperform other stocks over the long run, and that low price to book ratio firms outperform high price to book ratio firms (Fama and French 433). Fama and French state that "relations between average returns and size…and book-to-market equity are strong" (Fama and French 428). In addition to the factors of HML and SMB, Fama and French argue that Price/Earnings is another important factor, which will also be used in this project. They argue that "the earnings-price ratio is catch-all for omitted risk factors in expected returns" (Fama and French 444). Essentially, any factors and influences not accounted for in the three factor model should be visible within the P/E factor. Within the portfolio management industry, this model has become very popular in recent years. Many actively managed mutual funds and index funds now utilize a variant of the three factor model in their management practices (Fama and French 462).

Professional Practices

The text Quantitative Equity Portfolio Management by Ludwig Chincarini and Daehwan Kim (2006) is recognized as an industry standard for building quantitative models. It is a comprehensive, step- by-step guide which combines nearly the entire field of industry knowledge and practices. This text begins by illustrating the basic principles of quantitative active portfolio management and then clearly outlines how to build an equity portfolio using those powerful concepts. It provides clear explanations of topics ranging from basic models, factors and factor choice, and stock screening and ranking to fundamental factor models, economic factor models, and forecasting factor premiums and exposures. The text also includes deep coverage of portfolio weighting, rebalancing and transaction costs, tax management, leverage, market neutral strategies, Bayesian performance measurement and attribution, and the back testing process. This will be the primary resource used to construct the model for this project.

Although this text serves as a broad guide for the industry-accepted practices within the realm of quantitative equity portfolio management, this focused on factor choice, premiums, and the execution of the model, including performance measurement and attribution. The topics of leverage, tax management, and other secondary functions will not be utilized with detail in this endeavor.

The practices brought forth in this book are based on what the authors call the seven tenets of quantitative equity portfolio management outlined below in Table 1. All of their beliefs are based on the assumption that financial markets are somewhat inefficient. (Chincarini and Kim 21) They believe that there is always alpha, or excess returns, to be found in this field, and this is due to the fact that markets are not completely efficient. Essentially, there is a way to find excess returns in equities using statistical methods that are not yet accounted for widely in the pricing of a security.

Table 1: Tenets of QEPM (Chincarini and Kim 27)

Tenet 1	Markets are mostly efficient.
Tenet 2	Pure arbitrage opportunities do not exist.
Tenet 3	Quantitative analysis creates statistical arbitrage opportunities.
Tenet 4	Quantitative analysis combines all the available information in an efficient way.
Tenet 5	Quantitative models should be based on sound economic theories.
Tenet 6	Quantitative models should reflect persistent and stable patterns.
Tenet 7	Deviations of a portfolio from the benchmark are justified only if the uncertainty is small enough.

Although it is nearly impossible to incorporate every single piece of data available in financial markets into a stock prediction model, these authors argue there are ways to choose the most suitable factors.

For example, Chincarini and Kim assert that:

> The central, unifying element of quantitative equity portfolio management is the quantitative model that relates stock movements to other market data. Quantitative equity portfolio managers create such models to predict stock returns and volatility, and these predictions, in turn, form the basis for selecting stocks for the portfolio. (Chincarini and Kim 65)

Thus, the key to modeling quantitative portfolios is choosing the correct market data. Despite the fact that there are many software packages available to portfolio managers which deal with quantitative models, there is not a single model that is suitable for all types of equities. Each case varies greatly. For any given security, industry, or sector, factors which influence the prices will most likely differ, as will opinions and preferences of portfolio managers.

Chincarini and Kim refer to two basic types of quantitative models. The first is an economic factor model, which is based on broad based economic influences such as real GDP, inflation, commodity prices, and other macro factors. Models like this tend to be broader in their definition, and usually have a harder time zeroing in on stock price movements. (Chincarini and Kim 67) The second type of model is a fundamental factor model. This incorporates forces of influence which are specific to the firm or industry, and narrow the scope of the model significantly. Although both models are given great attention both in the industry and in the text, this project will focus on fundamental factor modeling within quantitative equity portfolio management.

Factor choice is extremely important to the effectiveness of the model. However, there are two main components to the quantitative model. Factor choice and factor premiums are both extremely influential in the overall effectiveness of the active model. The factor premium is the weight assigned to the given factor in modeling future predicted returns. Typically, this weight, or premium, is assigned based on historical regression analysis. This regression analysis can take a number of forms including the ordinary least squares approach and other types of multivariable regression models. The expected return of the equity security is then ultimately determined by the factor exposure multiplied by the factor premium. (Chincarini and Kim 68)

The element of data gathering is one of large scale. There are many different ways to gather historical stock data, and it is all based on the personal choices of the portfolio manager. A manager may choose to gather data for a certain index such as the Standard & Poor's 500, for a particular industry, or another grouping. The periodicity of the data is also a factor in determining the results of the model. (Chincarini and Kim 69). Depending on the frequency of the data (weekly, monthly, annually), the regression may reveal different factor premiums.

Once historical data is gathered and regression is performed, the quantitative portfolio manager can choose from a myriad of techniques to balance and weight the respective portfolio. The manager would, at this point, have expected returns, and also equity risk data.

As is widely understood, there are nearly countless methods of constructing a fundamental factor quantitative equity portfolio. The ultimate choice of construction methodology and theory comes to the portfolio manager. It is up to this person to decide which historical data to use, which factors to incorporate, which firms to analyze, and many other aspects. Among some influences to be considered in the decision making process are the ability to combine different types of factors accurately, overall ease of implementation, data requirement, consistency with economic theory, and intuitive appeal. (Chincarini and Kim 83) It is crucial that the chosen factors are able to function well together in order to predict future stock returns in a statistically significant manner. The ease of implementation is also of concern, since the portfolio manager's time is extremely valuable and scarce. The data requirements are also important because depending on the data chosen, the predicted returns will change. Also, the model must adhere to the sound economic theory which is believed by the portfolio manager. These assumptions are integral to the decision making process of crafting and executing the quantitative equity portfolio model.

When choosing fundamental factors, it is important to choose suitable factors which statistically explain historical stock returns, and are believed to do so into the future. This would, in theory, create statistical arbitrage. (Chincarini and Kim 92) As previously mentioned this model will focus on a few main fundamental factors which are widely believed to be predictive of equity returns. Those factors are price/EBITDA, price to earnings (P/E), and price/cash flow.

When building the fundamental factor model, a few things must first be understood. Essentially, the return of a stock is the payoff for taking a certain amount of risk. (Chincarini and Kim 185) In these models, the factor exposure measures the amount of risk a stock has in a certain factor. The premium of this factor quantifies the benefit of owning that stock given the associated risk. (Chincarini and Kim 185). Procedurally, once the historical returns and factor exposures are obtained, modeling can begin. Using a panel regression of the stock return on the factor exposure, the portfolio manager can derive the factor premium for the given factor. This can be determined using the OLS (ordinary least squares), MAD (minimum absolute deviation), or GLS (generalized least square) method of regression analysis. (Chincarini and Kim 188) The forecasted return for the equity security is then the product of the factor premium and its respective exposure. As the authors assert:

> A model is not usually an exact description of reality, only a good approximation of it. …Errors arise in any regression, and estimation of the factor premium is no exception. Yet we should strive to build models that reflect persistent and stable patters, as described in tenet 6….” (Chincarini and Kim 199)

When a portfolio manager decides to analyze stocks, they typically do not do so on a whim. Normally, they portfolio is held to a certain benchmark, such as the S&P 500, which they must maintain some consistency in relation to. Within a benchmark index are different types of underlying securities and firms. The industry standard for classifying different types of stocks is the Morningstar Style Box.

Originally developed in 1992, this classification matrix was intended to help mutual fund investors understand what types of funds they may be investing in (Morningstar 2002). By classifying a fund (or security) as a growth, core, or value firm with a small, mid, or large size, they could pinpoint the style of a given fund. This has since evolved to encompass individual stocks. Each firm falls into one of the nine style boxes based on its market capitalization and valuation factors.

The vertical axis measures size, or market capitalization. Large cap stocks collectively constitute the top 70% of the capitalization of each style zone. Mid-cap stocks are comprised of the middle 20%, and small cap stocks make up the remaining amount. The horizontal aspect of the box represents the firm style. The style of the firm is determined by the intersection of the growth score and the value score. The value score is a weighted average of 50% forward P/E, and 50% (weighted equally) price-to-book, price-to-sales, price-to-cash flow, and dividend yield. The growth score is a weighted average of 50% long-term projected earnings growth, and 50% (weighted equally) historical earnings growth, sales growth, cash flow growth, and book value growth. (Morningstar 2002) This multitude of factors is generally accepted to be an industry standard for classifying stocks within a given segment of the financial markets, based on the tendencies of the stock price and movements.

In two papers written by a cohort of State Street Global Advisors quantitative portfolio management experts, some interesting issues are brought up regarding the feasibility and methods of quantitative equity portfolio management. In one paper, the authors mention the notion of what they call "genetic programming" and its use in constructing quantitative models. Originally developed for the science community, genetic programming is used for the study of genetics. They have adapted this practice to the field of stock selection. The authors believe that the most challenging part of building a quantitative model with a high degree of accuracy lies within factor choice. They believe that genetic programming provides a means to determine which factors work well together in predicting stock returns. Although their literature does not detail the specifics of their model, it does include a basic understanding of the guiding principle behind their genetic programming. Different nodes, or "leafs" are used, and loaded into each are variables such as economic factors and events, financial ratios and figures, and technical factors (Becker, et al. 5). The nodes then come together, and using a natural selection approach, the model filters through to see which are most relevant in predicting stock prices. They mention that models such as this are relatively simple in theory, but involve vast amounts of input data to build the nodes.

The approaches used in the genetic programming method generate a stock selection model from the S&P500 index based on a low active risk tolerance investment style. (Becker, et al. 5) Essentially, the model uses natural selection theory to select stocks that lie in the "fat tails" of the normal distribution of equity returns. (Becker, et al. 9) According to their studies, this method of genetic programming proves to be statistically significant for the low risk tolerance active investment style. This model proves itself to be very effective, but at a limited scope. The flaws of this model lie in suitability. However, with the proper adjustments, such as different risk tolerances and portfolio indices, it should be able to be tailored to different portfolios, securities, and active risk tolerances.

In their second and more recent paper, Becker, Fox, and Fei illustrate a different model which is not based on solely genetic programming. Although they assert that the most difficult part of constructing a quantitative equity model is still factor selection, they use different methods to build their models. (Becker, et al. 3) Instead of relying on just genetic programming for stock selection, they realize that there are other important factors.

In addition to using just genetic programming for their stock selection models, the authors incorporated a multi-objective fitness function. (Becker, et al. 2) They incorporate multi-variable regression using the ordinary least squares (OLS) approach to predict returns in addition to genetic programming. Since the authors recognized that genetic programming methods alone were not well-balanced enough to provide highly accurate predictions, multi-variable regression was added in order to improve statistical significance. (Becker, et al. 15) By running various iterations of the model using many different factors coupled with the use of genetic programming, the researchers were able to generate more robust results and significance. (Becker, et al. 16)

Overall, this coupling of two different methods of constructing a quantitative equity portfolio is extremely drawn out, and is still not narrowly defined. Instead, it focuses on a larger benchmark such as the S&P500. Also, this method is claimed by the authors to work best during periods when value stocks are in favor. (Becker, et al. 14) However, this does not always occur, nor are the cycles of value and growth favor predictable. In order to be more accurate, it is generally accepted that the model be highly adaptive and customizable, as suggested by Chincarini and Kim. Also, the use of a model which proves to be effective during times when both value and growth stocks are in favor would prove to be more valuable in the quantitative equity portfolio management area of focus.

In summary, many unique and significant methods of quantitative equity portfolio management have been introduced by various researchers and experts; the most in depth of which being offered by Chincarini and Kim. The studies conducted by Becker, Fox, and Fei are certainly valuable to the field of active quantitative equity portfolio construction, but their drawbacks are simply too significant to overlook. Their effectiveness is tied to certain market cycles, whereas portfolio managers need models that work regardless of growth and value investing periods in which the two are mutually exclusive.

The strengths of the various strategies discussed lie in the statistical significance. Each strategy has its own respective benefits in terms of the types of securities or portfolios it best predicts returns for. However, none of the mentioned strategies are significant in predicting returns for all types of equities, which is to some degree understandable. However, the ability to make a model more flexible and customizable, such as those put forth by Chincarini and Kim, is the most widely effective method to predict security returns on a quantitative active basis. Also, the Fama-French three factor model has proven to be extremely effective and popular in the field of modern quantitative equity portfolio management. The fact that it takes into account unique factors which inherently limit various types of risk contributes to its success.

In order to determine whether the widely used factors within the industry are effective at forecasting stock returns, this study examined the most commonly used and understood factors used by professionals to predict future equity returns, as mentioned previously. These methods were then used to reveal if these traditionally accepted methods are statistically significant. This will contribute to the current field of knowledge by offering more insight on industry standards and their effectiveness, along with possible ways to improve on them. The goal was to pinpoint how effective these measures are at adding alpha to the decision making process in active quantitative equity portfolio management practices.

MODELING

As is previously mentioned, the framework of this quantitative model focused on the concepts of quantitative equity portfolio management, and did not incorporate other theories such as APT and CAPM. In order to construct a model, several choices had to first be made to narrow down the scope of analysis. The universe of securities had to be selected. After this was completed, data needed to be mined in order to generate the values for all of the fundamental factors involved. The Fama and French factors also had to be gathered for inclusion into the model. Once the necessary data was gathered, the model was assembled and executed.

In the interest of limited time and resources, the universe of this model was the DOW 30. This is an index of 30 industrial stocks that play large parts in the US economy. It was also assumed that data gathering would be more bountiful with stocks such as these, since there would generally be more data available. However, some of the stocks had gaps in certain data, so the original list of 30 was supplemented by a few other stocks, and some stocks were removed. The final analysis involved 26 securities, listed in the chart below.

AA	VZ	BA	CAT	UTX	WMT	CVX
KO	C	DIS	DD	EMC	MSFT	XOM
HPQ	HD	INTC	IBM	FCX	RIG	JNJ
MCD	MMM	COP	PG	T		

Once the stocks were selected, the data was gathered from the Compustat database for financial data. Data was compiled on a quarterly basis from March 31, 1996 to December 31, 2007. This gave 48 periods from a perspective of data analysis. The historical returns were gathered from Thomson Reuters. These returns were based on prices adjusted for splits and dividends. The factors for inclusion in the analysis were price/earnings, price/cash flow, and price/EBITDA. The Fama and French three factors were also included in the model.

In order to analyze statistical significance between the three fundamental factors and returns, the return data was lagged by 1 quarter. Essentially, this allowed the regression model to compare current fundamental factor values to future returns. Initially, 3 quarters of lagged returns were used in an effort to increase statistical significance. However, this proved to only cloud the model and did not offer any incremental increases in statistical significance. The second and third return lagged regressions were actually less significant, so they offered no value to the analysis. The choice to use 1-period lagged returns was then made in order to have a uniform approach to analysis and reporting. The underlying equation used to perform the regressions was as follows:

$$r_t = \alpha + \beta_{rt\text{-}1} + \beta_{PE} + E_t$$

$$r_t = \alpha + \beta_{rt\text{-}1} + \beta_{PE} + E_t + \beta_{FF} + \beta_{HML} + \beta_{SMB}$$

The first equation essentially states that the return for a stock includes alpha, or a measure of excess returns, the lagged returns coefficient, the fundamental factor coefficient (in this case, P/E ratio), and an error term. The second equation was the one used in regression because it included the Fama-French factors as control variables. The ending 3 terms signify the Fama-French beta, small minus big coefficient (SMB), and high minus low coefficient (HML). In order to test for statistical significance, ordinary least squares regression was performed within Microsoft Excel. The decision was made to use ordinary least squares regression over the panel data approach because time was important. In panel data, the times are not important, only the values of the data are. This model aimed to focus both on timing and the factors themselves, since this is inherently how the stock market works. To perform the regression, each of the 26 stocks was split into its own respective tab in order to make the analysis more manageable. Macros were used to automate the process of formatting and arranging the data. Once the data were in their respective sheets, 3 regressions were performed on each security. Across the 48 time periods, unique regressions were performed for each of the three fundamental factors. The regressions included the lagged return, the targeted fundamental factor, and the three Fama-French factors. Once this process was performed for each of the 26 involved securities, the results were reported in a summary tab. This summary took into account the coefficients for each factor, along with t-statistic illustrations. This data can be found in the appendix.

Since in reality stocks exhibit unique responses to various factors, it did not make sense to focus on every single regression coefficient and t-statistic. Instead, averages were calculated for each of the three factors. Instead of simply looking at the values for only the factor, values for the Fama-French factors were also included to observe any influence they may have had over the outputs from the modeling process.

RESULTS

The ordinary least squares regression (OLS) results for the three fundamental factors (P/E, P/EBITDA, P/CF) can be found in the appendices. When looking at the average predictive power, it becomes clear that within each of the three tested fundamental factors examined, the Fama-French factors were not significant predictors. They did, however, serve their purpose of mitigating tracking errors and firm-specific anomalies, they were not themselves significant predictors of returns for the stocks. This is important to the integrity of the modeling framework. If the Fama-French factors were proven to be significant predictors in isolation, the modeling would essentially be useless. Instead, these factors are an additional control tool.

When taking into account the significance of the targeted fundamental factors, some interesting results emerge. The coefficient, or weight of each factor, was observed along with the t-statistic. The t-statistic is simply the regression coefficient divided by the standard error. A high t-statistic indicates statistical significance.

As shown in Table 1 of the appendix, the price to earnings emerges as a fundamental ratio that is not statistically significant in predicting future stock returns. The average coefficient on the P/E ratio is 0.000151 with an insignificant average t-statistic of -0.005. This is likely due to the fact that the forward price to earnings ratios may be more accurate since they include forward-looking financial estimates. Quite simply, the price to earnings ratio of a stock only describes the way investors react to the firm's activities, and may not be a good way of predicting returns.

A second variable examined was the price to cash flow ratio. Table 2 shows the average coefficient across all stocks of 1.008 along with a t-statistic of 0.8007. This is more promising that the P/E ratio – with several companies showing that it is a useful predictor. INTC, VZ, IBM, and T all exhibit more significance than average for this factor. For these companies with a statistically valid parameter estimate, (how many stocks) this fundamental factor may indeed be a valid predictor of future stock returns. For the majority of stocks, however, the factor is insignificant. This mild form of significance may be due to the historical nature of the stock was well. If past performance is shown in this ratio, technically it should have no bearing on future performance. However, if the investor has a certain expectation of future cash flows, this ratio would be a good way to estimate a price.

The third fundamental factor of price to EBITDA examined proved to be the most significant within this model. Illustrated in Table 3, the regression yielded an average coefficient of 2.2236 along with a t-statistic of 1.149. A few stocks had higher significance than average, including VZ, C, DIS, DD, INTC, T, and WMT. Although the magnitude of the coefficient is relatively high, the t-statistic for most companies is below the 95% percent level of confidence. Generally, a t-statistic above 2 indicates strong statistical significance since the coefficient is twice as large as the standard error. The high coefficient in the case of P/EBITDA means that out of these three factors, it had the largest impact of the factors examined when predicting returns if it was significant in that company's regression. The average t-statistic across all firms indicates moderate significance in this case. This is a more accurate predictor of future stock performance than P/E because price to earnings takes into account much less information. Since the impact of interest, taxes, depreciation, and amortization can have a large impact on a firm, especially into the future, the P/EBITDA may be more valuable in valuation.

Overall, these results illustrate that these fundamental factors, when coupled with Fama-French factors for control, are not by themselves significant as predictors of future returns. Due to limited time and resources, the modeling used in this paper was scaled back. Models used by professionals, however, typically include many more factors, longer time periods, and a larger universe of stocks. The goal of this model was not to find the next hot stock, but rather to assess the components and methods of quantitative equity portfolio management.

Given these limitations, the results are fundamentally sound and represent a more formal examination of the QEPM models. Several theories were examined, and OLS regressions were conducted to examine the model's accuracy. The data gathering process was time consuming and tedious but the data was analyzed closely to avoid errors and remove questionable data to minimize errors. Although the sample size and universe were small relative to a professional money manager, it involved thousands of data cells. The sheer scale of this model alone serves as a microcosm for the way models used by investment professionals work. This is why the model discussed in this study is a fair and accurate representation of the concepts and framework currently in use.

CONCLUSION

The purpose of this paper was to compile and examine industry QEPM practices and compile some data to examine the strength of these theories. This study and modeling confirmed that there are many different ways to value securities, and that there is no one “right way” to do so. In fact, if two people are assigned to build a model to predict returns for a given stock, it is highly unlikely that they will emerge with similar results. Quantitative equity portfolio management models are highly unique and customizable. Every manager has a unique style to value securities when building an underlying portfolio.

This study accurately built a small scale active quantitative equity valuation model. If this model were expanded to involve a much larger investment universe, it may produce more valuable results. Incorporating more factors may also improve statistical significance and predictive power since the returns would be checked against a multitude of different possible factors. This model also shows that limited information may not yield very strong results. For example, if a portfolio manager used this model to evaluate a few stocks, he or she may not end up finding any worthwhile investments. Although the model worked well, not enough inputs and variables may have been incorporated.

In order to expand this model and research for future applications, factors could be added, different time periods and industries could be analyzed, and a larger universe of investments could be examined. Moving from Microsoft Excel to commercially available statistical software would simplify the data management and make it much more scalable, workable and efficient.

The purpose of this study was not to offer a dispute-settling answer to which factors and models work best in predicting stock returns, but rather to review their effectiveness and applications on a broad scale. To achieve these objectives, I choose three fundamental factors and tested them on 26 stocks. Although the project was limited in scope, much of this study can be applied to the investment field. The paper provided me with a strong knowledge of quantitative equity portfolio management. The highly customizable models can prove to be successful in conjunction with good management judgment. It is clear, however, that quantitative equity portfolio management is a powerful tool that can be expanded on a large scale to add value to the work of any active portfolio manager and I believe that they have a valid place in the work of active managers.

APPENDICES

P/E: $r_t = \alpha + \beta_{rt-1} + \beta_{PE} + E_{t\,+}\,\beta_{FF} + \beta_{HML} + \beta_{SMB}$

	PE							
	COEFF	*T-STAT*	*MKT*	*T-STAT*	*SMB*	*T-STAT*	*HML*	*T-STAT*
AA	0.002494	1.578339	0.009155	1.549126	0.002444	0.388021	0.006035	0.717686
VZ	6.77E-05	0.960797	0.006891	1.785269	-0.00147	-0.36314	0.000695	0.128139
BA	-0.00074	-1.38067	0.008407	1.320541	0.007454	1.124851	0.015115	1.707255
CAT	0.002639	1.024271	0.000336	0.053511	0.006075	0.912667	0.001484	0.168232
CVX	0.000772	0.956471	0.004103	1.110911	0.004556	1.169228	-0.00019	-0.03574
KO	7.56E-05	0.609287	6.01E-05	0.012447	-0.00282	-0.55289	0.005824	0.877554
C	-0.0029	-1.38352	0.007539	1.294845	-0.00011	-0.01791	0.005136	0.639259
DIS	-0.00073	-2.22455	0.017958	3.711466	-0.00491	-0.96	0.013113	1.950809
DD	-0.00034	-2.08433	-0.00182	-0.36413	0.00148	0.284649	0.003209	0.466401
XOM	-0.00134	-1.04338	0.006195	2.031967	-0.00116	-0.35031	0.004603	1.003967
HPQ	-0.00069	-1.38854	0.007116	0.947687	-0.01076	-1.32558	0.003888	0.350746
HD	0.001199	0.748851	0.014711	2.373999	-0.00834	-1.31415	-0.00268	-0.31734
INTC	-0.00065	-1.04528	0.006565	0.687941	-0.01238	-1.37541	-0.01154	-0.94599
IBM	-0.00041	-1.88683	0.001021	0.20553	-0.00822	-1.62431	-0.00418	-0.62131
JNJ	0.000136	0.502457	-0.00107	-0.30121	0.002204	0.583027	-0.00104	-0.20309
MCD	0.000669	0.402187	0.002472	0.436954	-0.00504	-0.92132	-0.00895	-1.22893
MMM	-0.00115	-0.66716	-0.00206	-0.54522	0.003479	0.868338	0.004496	0.847787
COP	0.000525	0.798025	0.005559	1.328148	0.010367	2.291479	0.00855	1.412756
PG	0.001092	1.262851	0.002835	0.650674	-0.00142	-0.3124	0.009972	1.647607
T	0.000813	1.173196	0.008011	1.810998	0.00066	0.139343	0.00451	0.719034
UTX	-0.00189	-2.18433	0.005783	1.260433	0.005193	1.073385	-0.00227	-0.33933
WMT	0.002368	1.350312	0.008884	1.782108	-0.00326	-0.61313	-0.00564	-0.78871
EMC	0.001555	2.245972	0.030461	3.251988	-0.01305	-1.3091	0.003432	0.254028
MSFT	9.21E-05	0.907073	0.004057	0.613379	-0.01331	-1.90347	-0.00437	-0.47214
FCX	1.76E-05	0.029739	0.002487	0.226665	0.002786	0.230109	0.008296	0.53152
RIG	0.000248	0.608807	0.012877	1.51242	0.016467	1.81397	0.012519	1.046746
AVERAGE	**0.000151**	-0.005	0.006482	1.105709	-0.00089	-0.07939	0.002693	0.366036

Table 1

P/CF: $r_t = \alpha + \beta_{rt-1} + \beta_{CF} + E_{t\,+}\,\beta_{FF} + \beta_{HML} + \beta_{SMB}$

	CF							
	COEFF	*T-STAT*	*MKT*	*T-STAT*	*SMB*	*T-STAT*	*HML*	*T-STAT*
AA	0.400252	1.415351	0.008174	1.374148	0.00129	0.205779	0.003095	0.37025
VZ	2.736419	1.387018	0.00579	1.517965	-0.00065	-0.16174	0.000731	0.136886
BA	0.013983	0.044196	0.006973	1.085135	0.007223	1.055498	0.014128	1.555356
CAT	0.106195	0.32091	2.41E-05	0.003786	0.007553	1.072108	0.001953	0.219094
CVX	-1.23297	-1.62717	0.005214	1.418668	0.003094	0.792494	-0.00041	-0.08016
KO	-0.19273	-0.30112	-0.00036	-0.07426	-0.00263	-0.49834	0.006193	0.93424
C	-0.02894	-0.03993	0.006027	1.0266	0.000243	0.039151	0.005437	0.653254
DIS	-0.2382	-0.35128	0.020027	3.844055	-0.00321	-0.60115	0.01344	1.886861
DD	0.07747	1.191602	0.001027	0.203848	0.00432	0.803761	0.00614	0.859208
XOM	0.615489	0.203114	0.005919	1.899289	-0.00018	-0.05485	0.006435	1.473839
HPQ	0.694156	0.737783	0.008117	1.065443	-0.01136	-1.34035	0.002545	0.217503
HD	1.519737	1.157784	0.014463	2.383516	-0.00798	-1.26773	-0.00292	-0.34913
INTC	8.014223	2.710899	0.008664	1.088834	-0.00619	-0.72426	-0.00857	-0.77129
IBM	2.075935	2.196181	0.003388	0.718026	-0.0067	-1.32039	-0.00399	-0.60195
JNJ	1.078362	1.127041	-0.00126	-0.35885	0.002665	0.710263	-0.00146	-0.29657
MCD	1.216312	1.093638	0.002422	0.467041	-0.00432	-0.79385	-0.00924	-1.28416
MMM	-0.08947	-0.24751	-0.00186	-0.4901	0.00317	0.793203	0.004852	0.89871
COP	-0.83108	-1.16096	0.006079	1.460403	0.008659	1.948151	0.006888	1.178315
PG	1.450481	1.396061	0.004626	1.068921	-0.00076	-0.16596	0.011707	1.881616
T	2.908485	1.560081	0.00712	1.658554	-0.00025	-0.05618	0.002342	0.387735
UTX	1.108668	3.036496	0.004943	1.12755	0.008494	1.790455	0.003011	0.488005
WMT	3.38339	2.022514	0.007751	1.606879	-0.00319	-0.6221	-0.00885	-1.30283
EMC	0.733052	2.416865	0.026081	2.790644	-0.01251	-1.26344	-0.00382	-0.2935
MSFT	0.718034	0.711747	0.002888	0.436246	-0.01168	-1.66198	-0.0037	-0.39254
FCX	0.005342	0.023178	0.002405	0.226525	0.002665	0.23754	0.008158	0.546746
RIG	-0.02919	-0.20647	0.012783	1.472539	0.015384	1.706911	0.012211	1.013817
AVERAGE	**1.008208**	0.800693	0.00644	1.116208	-0.00026	0.023961	0.002551	0.358819

Table 2

P/CF: $r_t = \alpha + \beta_{rt-1} + \beta_{EBITDA} + E_{t} + \beta_{FF} + \beta_{HML} + \beta_{SMB}$

	EBITDA							
	COEFF	*T-STAT*	*MKT*	*T-STAT*	*SMB*	*T-STAT*	*HML*	*T-STAT*
AA	0.878646	1.1941	0.006803	1.099843	0.00244	0.379497	0.004545	0.539908
VZ	2.846192	1.268555	0.005445	1.403448	-0.00069	-0.17233	0.000981	0.183447
BA	0.307462	1.021775	0.005384	0.823962	0.006392	0.947293	0.01266	1.400649
CAT	2.209013	2.050579	-0.00012	-0.01976	0.00699	1.095696	0.001367	0.160753
CVX	-0.82547	-1.09974	0.004794	1.287452	0.003134	0.772346	-0.00166	-0.31175
KO	1.498317	0.810222	-0.00138	-0.28774	-0.00109	-0.21354	0.006905	1.04013
C	10.20751	2.386485	0.003574	0.641182	0.000352	0.060947	0.005199	0.675136
DIS	8.271786	2.939731	0.015323	3.17615	-0.00663	-1.32551	0.004559	0.641037
DD	3.245737	1.176239	0.000958	0.190145	0.004066	0.760303	0.005823	0.818337
XOM	0.893258	0.403124	0.005811	1.863595	-2E-05	-0.00601	0.006682	1.51328
HPQ	-0.18183	-0.11351	0.008208	1.002965	-0.01354	-1.64125	-0.00113	-0.10427
HD	0.852083	1.122133	0.014486	2.383809	-0.00803	-1.27402	-0.0027	-0.32298
INTC	6.574012	2.296286	0.007421	0.900449	-0.00653	-0.74498	-0.006	-0.52588
IBM	2.584986	2.271986	0.004005	0.85144	-0.00754	-1.51015	-0.00468	-0.70739
JNJ	1.971756	1.726369	-0.00191	-0.54794	0.002872	0.784189	-0.001	-0.20699
MCD	1.191984	0.854062	0.002294	0.433185	-0.00402	-0.71956	-0.00815	-1.12319
MMM	0.145677	0.256941	-0.00182	-0.47876	0.003076	0.767164	0.004544	0.851694
COP	-0.73026	-1.38481	0.006498	1.561052	0.008667	1.972352	0.006675	1.148104
PG	2.489825	2.08805	0.004035	0.968118	-0.00176	-0.39952	0.010618	1.806444
T	3.915053	1.198404	0.006466	1.480122	-0.00035	-0.076	0.002605	0.426702
UTX	1.397312	2.820224	0.003929	0.878146	0.008887	1.82979	0.004293	0.681359
WMT	6.705237	2.31449	0.006388	1.328202	-0.0022	-0.4289	-0.00569	-0.84328
EMC	0.155698	1.363596	0.025388	2.526414	-0.01841	-1.78376	-0.00694	-0.50226
MSFT	1.404226	1.531718	0.001834	0.281207	-0.0114	-1.66824	-0.00338	-0.37051
FCX	-0.15428	-0.27943	0.002831	0.264139	0.003161	0.27879	0.008896	0.587624
RIG	-0.0413	-0.34079	0.012928	1.497878	0.015094	1.664502	0.01172	0.978761
AVERAGE	**2.223562**	1.149107	0.005753	0.981104	-0.00066	-0.02503	0.002182	0.324417

Table 3

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