AN EXAMINATION OF THE RELATIONSHIP BETWEEN THE CAPITAL ASSET PRICING MODEL'S SYSTEMATIC RISK INDICATOR AND STOCK RETURNS

by

Kacy Crowe

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

Liberty University, School of Business

December 2019

Abstract

The purpose of this quantitative study was to examine the relationship between the Capital Asset Pricing Model's risk indicator beta and the average monthly returns for stocks in the S&P 100. The problem addressed was that low beta stocks produced higher returns than high beta stocks. The study was conducted using the S&P 100 constituents. The study expanded the research literature regarding the beta anomaly and found a statistically significant result for an association between beta and average monthly returns for stocks in the S&P 100. The study has implications for investors and financial practitioners as to whether beta can still be used as a risk indicator.

Key words: Capital Asset Pricing Model, systematic risk, beta, unsystematic risk

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____ Date:____________

Dr. Adam Sullivan, Chair

____ Date:____________

Dr. Gene Sullivan, Committee Member

____ Date:____________

Dr. Edward M. Moore, DBA Program Director

Dedication

This dissertation is dedicated to my wife Tracey and my daughter Josie. They have sacrificed time with me for countless nights and weekends. Your encouragement, love, and grace carried me through this process. Without your support I would not have finished. Thank you for everything you did to encourage me and lift me up.

Acknowledgements

I would like to thank my wife and daughter for their unending support throughout this challenge. Tracey, you sacrificed, mentored, and encouraged me and without you I would not have finished. Josie, you ensured I had enough time to complete my work even at the expense of time we could have shared together. I look forward to being your dad again. I also want to thank all my extended family for understanding when I had to write or listened when I was stressed. Thank you for your words of encouragement and not giving up on me.

I would like to thank all those at Liberty University who have come in contact with my dissertation. Thank you Dr. Sullivan, for picking up at such a late stage to help me through to completion. Thank you Dr. Moore, for the early morning phone calls and working sessions to ensure I was on track and could finish. Thank you Dr. Candy for all your encouragement. I would also like to thank my cohort, especially Carol, for the continued support throughout this process. I am eternally grateful.

Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

According to the Capital Asset Pricing Model (CAPM), high-beta securities generate higher returns in a rising market than low-beta securities. The results of a longitudinal study, conducted over a forty-year period, contradicted the CAPM by finding a positive relationship between low-beta securities and higher returns (Baker, Bradley, & Taliaferro, 2014). This finding challenges the reliability of the CAPM since the researchers found that low-beta stocks outperformed high-beta stocks. Since beta is the estimated measure of risk for stocks, the findings contradict investors' belief that investing in high-risk stocks will generate higher returns. Stocks that produce higher returns but have overall lower risk are referred to as the low-beta anomaly (Blitz, Falkenstein, & Vilet, 2014).

Blitz, Falkenstein, and Vilet (2014) examined the relationship between low-beta anomaly and a range of variables that contribute to the CAPM (such as leverage, estimation intervals, investor risk aversion, complete information, and perfect markets) and concluded that beta is an inadequate measure upon which to base risk premiums. Beta coefficients are determined by utilizing linear regression over time to compare the volatility of an asset to overall market volatility (Mayo, 2008). However, the absence of a standardized method for gathering and analyzing data has resulted in varying published beta coefficients (Jacobs & Shivdasani, 2012). Financial entities gather data at different intervals to calculate beta estimate and the differences in methodology, and scale sensitivity may lead to mispricing and over-exposure to risk (Jacobs & Shivdasani, 2012).

Baker, Bradley, and Wurgler (2011) compared high-beta, high volatility underperforming stocks with low-beta, low volatility stocks and observed a decline in beta and stock performance since 1969. Baker et al. concluded that investment managers could exploit high-beta returns by benchmarking risk although there is no incentive for them to exploit the mispricing of low-beta stocks because of the length of time securities are held for long-term gains. Blitz et al. (2014) termed the phrase volatility effect to describe the weak relationship between and predictive power of securities' volatility on risk return. They argued that the volatility effect, or low-beta anomaly, had a strong positive correlation with low-beta stocks that outperformed high-beta stocks in equity markets. Blitz et al.'s findings supported earlier research that suggested that the integrity of data utilized to examine the relationship between high-beta securities and returns was open to challenge (Fama & French, 1992). Blitz et al. further argued that the root of the inaccuracies centered within the CAPM's assumptions surrounding the input of cross-sectional data, no constraints, investor risk aversion, complete information, and perfect markets. While acknowledging its usefulness, Fama and French (1992) argued that beta is unable to identify systematic risk through cross-sectional observations and, therefore, is unable to capture portfolio risk.

Background of the Problem

Researchers suggest that the low-beta anomaly is evidence that the CAPM is flawed. The statistical relationship between risk and return also indicates that investment managers may be making decisions based on inaccurate reporting of beta values. Fama and French (1992) built on the seminal work of Haugen and Heins (1975) to highlight the inaccuracy of the risk-return correlation and how beta lacked predictive power in how risk contributed to returns. Further, the relationship between beta and security returns was flat or inverse when firm size and leverage were considered (Fama & French, 1992). Blitz et al. (2014) found a higher rate of return for low-beta securities when investor risk and estimation periods are included in the analysis and found that oblique behaviors contributed to the low-beta anomaly.

Baker et al. (2011) claimed the low-beta anomaly to be one of the most significant irregularities in modern finance. These researchers also claimed that over-confidence and excessive exposure to high-beta stocks result in greater risk and overall loss. Xi, Sullivan, and Garcia-Feijoo (2016) investigated the role of systematic risk in calculating beta and concluded that investor mispricing of beta caused the low-beta anomalies. Currently, there is no consensus among financial institutions on the most accurate beta estimation for predicting security returns. With increasing availability and access to data, researchers are questioning the best option for calculating risk.

Researchers have not found a statistically significant correlation between risk and market returns (Blitz et al., 2014; Fama & French, 1992; Fama & MacBeth, 1973; Sanghi & Bansal, 2014). Differences in the sensitivity of interval level measurement scales for observing beta values affect the pricing of risk and the mispricing of securities over time. Baker et al. (2014) found a negative correlation between beta estimates and market returns when using five-year trailing averages with a frequency of monthly returns over a forty-year period. Baker et al. (2014) concluded that beta may be the wrong measure of risk and considered irrational investor behavior to cause the low-beta anomaly.

Fama and MacBeth (1973) found that beta captured risk in a two-factor model consistent with efficient markets although "stochastic non-linearities" also existed which presented as challenges to assumptions of beta and the CAPM (p. 633). Hence, they concluded that investors should minimize risk by diversifying portfolios and suggested these non-linearities were caused by the estimation intervals used to calculate the beta coefficient. When beta is estimated using stock return data older than 1969, the relationship between beta and market returns begins to show a negative or no correlation (Fama & French, 1992). Hence, given the evidence that beta may be an inaccurate measure of risk, further research is required to understand its relationship to risk, so investment managers can provide better-informed advice to clients.

Problem Statement

The general problem to be addressed is the beta anomaly, in which low beta stocks outperform high beta stocks, resulting in a situation that is in direct conflict with investors' expectations based on the CAPM. Elmiger & Elmiger (2018) stated that the performance anomaly of low beta stocks has created an asset-pricing puzzle and been the driving force behind an increased research focus on the CAPM beta. According to Baker et al. (2014), returns from low-beta stocks outperformed returns from high-beta stocks from 1963 through 2012. This is contrary to the assumption of the CAPM that stocks with a higher (lower) beta should produce higher (lower) returns, which would then justify an increased (decreased) risk premium. Neslihanoglu, Sogiakas, McColl, and Lee (2017) explained that the mechanics of the CAPM rely heavily on unrealistic expectations from dynamic markets that lack linearity, which has created multiple criticisms of the CAPM and beta. The specific problem to be addressed is whether beta, as a component of the CAPM, accurately indicates risk for stocks listed in the Standard and Poor's (S&P) 100 stock index.

Purpose Statement

The purpose of this quantitative correlational study is to examine the relationship between beta and risk using the CAPM and equities from the S&P 100. According to the CAPM, high-beta stocks produce a higher rate of return compared to low-beta stocks in a perfect market (Hong & Sraer, 2016). Beta is a measure of systematic risk that is difficult to diversify and is represented by the slope of a linear regression analysis plotting market returns (Kadan, Liu, & Liu, 2016). Based on the variability from previous research regarding the statistical significance between market returns and benchmark indexes, the relationship between beta and systematic risk needs further examination. The varying statistical relationship has been the foundation to establish a portfolio's risk premium and the expected return for investors (Cederburg & O'Doherty, 2016). There is no conclusive evidence cited in the literature that beta is an accurate reflection of systematic risk. When calculating beta, Kadan et al. (2016) highlighted discrepancies found when risk estimations used portfolios with distribution anomalies, such as market disasters. Hong and Sraer (2016) highlighted the discrepancy between beta and market returns and focused on the over price of high-beta assets compared to overall market returns. Kadan et al. argued beta only used the variance of risk to define systematic risk and did not reflect other market conditions.

Nature of the Study

The research methodology chosen for this study is a quantitative correlational design because it is the most conducive for use with large samples drawn from archival or secondary data (Creswell, 2013). The research methodology, considered the most concrete section of a research study, establishes an explicit part of the research proposal that grounds the study in process and procedures to answer a pending question (Creswell, 2013). Factors to consider when choosing the best method and design for scholarly research include the goals of the study, the purpose of the study, and the type of data gathered. There are three research methods: quantitative, qualitative, and mixed methods. Creswell (2013) described quantitative research as grounded in numerical data and close-ended questions used to answer research questions. Stake (2010) portrayed quantitative research as relying heavily on linear characteristics and statistical analysis to determine if a relationship exists between research variables.

Discussion of Method. Creswell and Creswell (2018) explained that the three research methods (quantitative, qualitative, and mixed methods) are not inflexible opposite designs but a representation of different perspectives of the research spectrum. Qualitative research is on one end of the research spectrum with quantitative research on the other end of the research spectrum (Creswell & Creswell, 2018). Mixed methods reside in the middle of the research spectrum as it incorporates both qualitative and quantitative attributes (Creswell & Creswell, 2018). Accordingly, the research method is viewed as a scientific procedure for gathering and analyzing problems that exist in research environments.

Quantitative research tests theories using numbered data with statistical procedures to examine if a relationship exists between variables (Creswell & Creswell, 2018). Creswell (2013) described quantitative research as a method to test objective theories by using statistical analysis to measure the relationship between differing variables. The quantitative research method is most appropriate because the purpose of this study is to examine if a relationship exists between two variables using statistical analysis to answer the closed-ended research questions, replicating similar work in asset pricing research (Bilinski & Lyssimachou, 2014; Bollen, 2010; Chaudhary, 2016; Fischer, Blanco-Fernandez, & Winker, 2016; Stivers & Sun, 2016). Simon and Goes (2013) depicted quantitative research as numerical data used to drive conclusions based on statistical analysis. Barczak (2015) posited quantitative research as a deductive process in which a hypothesis is developed from a theory and tested with data to accept or fail to accept the null hypothesis. Comparatively, qualitative research and mixed methods would not be appropriate for this study.

Qualitative research uses more open-ended questions framed in words, seeking to understand a problem in social or human groups (Creswell & Creswell, 2018). Qualitative research tends to be more inductive, while quantitative research is more deductive in nature (Simon & Goes, 2013). The deductive nature of this study aligns more closely with quantitative approach because the research questions are closed-ended and require statistical analysis to determine if a relationship exits. Qualitative research relies on human perception and comprehension, compelling researchers to use surveys or interviews to gather data (Stake, 2010). Gelling (2015) described qualitative research as a method to explore the human and social experience and the factors that contribute to those experiences. Creswell (2013) contended that qualitative researchers are the key instruments in collecting data from participants and transforming the information gathered into a theoretical lens to describe a phenomenon, whereas quantitative researchers use statistical analysis to answer research questions.

Creswell and Creswell (2018) stated that qualitative research is designed using words rather than numbers. Quantitative researchers capture numerical data with an instrument, while qualitative researchers capture data through observational settings (Creswell & Creswell, 2018). Qualitative methodology allows the researcher to formulate assumptions by inquiring about situations or behaviors based on activities in a natural setting (Houghton, Murphy, Shaw, & Casey, 2015). The qualitative research method is not appropriate for this study because the purpose of this study is to examine historical data to answer the research question with statistical analysis.

Mixed methods research, on the other hand, uses a combination of both qualitative and quantitative research characteristics by integrating the data to answer philosophical and theoretical assumptions (Creswell & Creswell, 2018). Clark (2017) stated that mixed methods research can help to better understand research problems by utilizing the strengths of both the quantitative and qualitative approaches. Researchers understand that all methods have bias, so the combination of the qualitative and quantitative methods is an attempt to minimize the bias in research (Creswell & Creswell, 2018). Stake (2010) described the mixed methods research approach as a means to understand a problem and improve the quality of knowledge surrounding the problem. Using mixed methods research requires a technical understanding of the philosophical and paradigmatic designs to research (Simon & Goes, 2013). The mixed methods approach uses both qualitative human introspection and quantitative numeric data woven into a single study, which adds rigor and triangulates the data for a more holistic understanding of the problem being researched (Halcomb & Hickman, 2015). The purpose of this study is to examine the relationship between two research variables, using historical data. Human participants will not be observed to answer philosophical assumptions or open-ended questions, so mixed methods would not be appropriate for this study.

Discussion of Design. Quantitative research features four distinct designs: correlational, descriptive, causal-comparative, and experimental (Creswell, 2013). The correlational design is most appropriate for this study because the researcher will use statistical analysis to explore the relationship between beta and market returns. Correlational research is used to evaluate the relationship between variables to determine if a relationship exists and whether predictions can be made using regression equations (Simon & Goes, 2013). Correlational research design can also include the use of archival data. Since the correlational design is used to determine if a relationship exists between variables by using statistical regression analysis, this was the most appropriate design for this study.

The descriptive design is the study of a phenomenon without intervening or modifying the phenomenon (Simon & Goes, 2013). Researchers typically do not start with a hypothesis; rather, the hypothesis is developed after the data collection. A descriptive design is based on characteristics of a population and researchers typically use systematic information to develop a hypothesis after measuring the phenomena with limited manipulation to variables (Creswell, 2013). With descriptive design, researchers seek to establish the what, when, where, and how often a phenomenon occurs by establishing an association between variables (Creswell & Creswell, 2018). Often with descriptive design, little is known about a phenomenon and the researcher categorizes the frequency at which the phenomenon occurs (Sousa, Driessnack, & Mendes, 2007). As the purpose of this study is to determine if a relationship exists between two research variables, and since observational data will not be used to develop a hypothesis of the current state of a phenomenon, the descriptive design is not suitable for this study.

The causal-comparative design is used to find the cause and effect relationship between two or more groups in which the variables are not manipulated. Lenell and Boissoneau (1996) defined causal-comparative research as the attempt to discover how a phenomenon occurs, isolating the cause of an observed behavior. Causal-comparative design also incorporates past events to compare against future results (Simon & Goes, 2013). The causal-comparative design, also referred to as the quasi-experimental design, has randomly assigned participants that have manipulated variables to determine a causal relationship (Creswell, 2013). The causal-comparative design seeks to establish a cause and effect relationship by manipulating the independent variable and administering to a control group (Simon & Goes, 2013). The results are then measured against a group not exposed to the independent variable. As the purpose of this study is to use historical data from two research variables to conduct statistical analysis, the causal-comparative design was not applicable for this study.

The experimental design is geared toward developing new theories by following a strict analysis of a sample population while adhering to strong research stages, which allows researchers to have the greatest amount of control (Simon & Goes, 2013). Experimental design is similar to causal-comparative design, as the researcher tries to determine the cause and effect relationship; but in experimental design, the researcher manipulates the variables used in the study (Creswell, & Creswell, 2018). Researchers use experimental design when testing the effect of a treatment and the resulting outcome, and it is considered the most sophisticated research method (Creswell, 2013). Experimental design is often used when developing a new theory (Creswell, 2013). As the purpose of this study is to conduct statistical analysis between two research variable using historical data from individual stocks in the S&P 100 and is not intended to determine the effects of the independent variable on the dependent variable, the experimental design was not a proper fit for this study.

Summary of the nature of the study. The nature of the study section defined the research method and design for this research project. The researcher explained the varying research methodologies and why the quantitative correlational research method and design were the most appropriate for this study. A quantitative correlational research method and design is the most appropriate for this study due to the researcher using archival numerical data to answer the research questions. Next, the research questions and the theoretical framework are addressed.

Research Questions

The researcher seeks to determine whether beta is a suitable measure of risk for individual common stocks. Since the introduction of the CAPM, researchers have waivered on whether beta accurately captures the risk of securities as evidenced by greater returns for higher risk. The research question for this study is designed to evaluate the relationship between systematic risk of the CAPM (beta) and actual returns for the S&P 100 common stocks, as well as examine the relationship between beta and the industry sectors of the S&P 100.

RQ1: Is beta an accurate indicator of risk or excess returns for individual stocks listed in the S&P 100 index when compared to the S&P 500 index as a benchmark?

RQ2: Are any of the three beta categories (low, strong, & high) a more accurate indicator of risk or excess returns for individual stocks listed in the S&P 100 index when compared to the S&P 500 index as a benchmark?

RQ3: Is beta a better indicator of risk or excess returns for the eleven industry sector stocks listed in the S&P 100 index compared to the S&P 500 index as a benchmark?

Hypotheses

H1: There is a statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the three beta category.

H_o1: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the three beta category.

H_o1a: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the low beta category.

H_o1b: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the strong beta category.

H_o1c: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the high beta category.

H2: There is a statistically significant difference in average monthly returns within the three beta categories (low, strong, & high).

H_o2: There is no statistically significant difference in average monthly returns within the three beta categories (low, strong, & high).

H3: There is a statistically significant association between average monthly returns for stocks in the S&P 100 and beta.

H_o3: There is no statistically significant association between average monthly returns for stocks in the S&P 100 and beta.

H_o3a: There is no statistically significant association between average monthly returns for stocks in the S&P 100 low beta category and the beta for the low beta category.

H_o3b: There is no statistically significant association between average monthly returns for stocks in the S&P 100 strong beta category and the beta for the strong beta category.

H_o3c: There is no statistically significant association between average monthly returns for stocks in the S&P 100 high beta category and the beta for the high beta category.

H4: There is a statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the 11 Global Industry Classification Standard (GICS) stocks in the S&P 100.

H_o4: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the 11 Global Industry Classification Standard (GICS) stocks in the S&P 100.

H_o4_a: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the energy sector stocks in the S&P 100.

H_o4_b: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the materials sector stocks in the S&P 100.

H_o4_c: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the industrials sector stocks in the S&P 100.

H_o4_d: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the consumer discretionary sector stocks in the S&P 100.

H_o4_e: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the consumer staples sector stocks in the S&P 100.

H_o4_f: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the health care sector stocks in the S&P 100.

H_o4_g: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the financial sector stocks in the S&P 100.

H_o4_h: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the information technology sector stocks in the S&P 100.

H_o4_i: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the telecommunications services sector stocks in the S&P 100.

H_o4_j: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the utilities sector stocks in the S&P 100.

H_o4_k: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the real estate sector stocks in the S&P 100.

Theoretical Framework

The theoretical framework for this quantitative correlational research is Markowitz' (1952) seminal work on Modern Portfolio Theory (MPT) that emphasizes the benefits of diversifying risk by combining or pooling assets to minimize risk and maximize returns (Klein, Daza, & Mead, 2013). An efficient portfolio generates higher returns with relatively low risk compared to portfolios with low returns (Lydenberg, 2016). Conversely, an inefficient portfolio generates lower returns with similar risk constraints compared to other portfolio returns. Although MPT achieves general portfolio selection, it does not completely diversify risk (Lee, Cheng, & Chong, 2015). Recognizing that MPT offered only partial explanations for risk and market behavior, Sharpe (1964) developed the CAPM to account for the role of risk in stock returns. Fama and French (2004) described the CAPM as an algebraic function that predicts the relationship between risk and expected return. Kim and Kim (2016) support the CAPM as an extension of MPT and an efficient means of calculating risk.

Systematic and Unsystematic Risk. Financial institutions define risk as the uncertainty that investors incur when exposed to capital markets (Kim & Kim, 2016). There are two types of risk associated with securities: systematic risk and unsystematic risk. Systematic risks are portfolio factors that cannot be diversified away and affect market returns when compared to other similar securities (Mayo, 2011). Systematic risk, also called volatility or market risk because it influences all securities, cannot be diversified out of a portfolio (Sanghi & Bansal, 2014). Two examples of systematic risk are inflation or interest rate changes.

Unsystematic risks are factors that can be diversified out of a portfolio and only affect the individual security or a specific industry, such as an employee strike or government regulations (Mayo, 2011). Unsystematic risk does not affect the overall market in the same way as systematic risk and its influence can be minimized through portfolio diversification (Sanghi & Bansal, 2014). Financial professionals have an interest in mitigating risk through diversification to minimize exposure to investments and to maximize returns (Kim & Kim, 2016).

CAPM. The CAPM correlates a relationship between systematic risk and the expected return of a market security. Investors use the CAPM to price risky securities; determine the cost of capital, and the expected returns of capital projects. The CAPM provides a method for investors to price risky securities and compensate for a higher rate of return, which consequently produces a positive linear relationship between expected risk and the expected stock return (Dawson, 2015). Investors who use the CAPM assume a reduced risk premium when grouped with individual securities in a portfolio with a direct correlation between beta risk and market returns (Blitz et al., 2014).

Investors who use the CAPM are assumed risk averse and seek to minimize risk while maximizing returns (Fama & French, 2004). Financial practitioners embrace the CAPM as the method to calculate risk and expected return for portfolios due to the simplified methodology. Dawson (2015) argued that the CAPM removes the need for investors to complete an expansive investigation into the organizations with which they plan to invest. The CAPM is built upon several assumptions about the investor. These assumptions are that the investors: are rational and risk-averse; focus on expected return and risk; acquire knowledge regarding the future of expected returns; can borrow or lend at a risk-free rate of return; and invest over one holding period (Dawson, 2015). Dempsey (2013) claimed that investors have become over reliant on the CAPM due to the assumption that investors are rational. The volatility and irrationality of market behaviors highlight the inconsistencies in empirical research that contradicts the assumption of investor rationality (Dempsey, 2013).

The CAPM, which is easy to compute, extends the relationship between risk and return by adding the risk-free rate of return, helping financial professionals to price risky securities (Dimson & Mussavian, 1999). The interest rate on the three-month U.S. Treasury Bill or T-Bill is factored for the risk-free rate. The T-Bill, considered the least risky investment, is backed by the full faith and credit of the U.S. government.

The equation (Mayo, 2011) for the CAPM represented for individual securities are:

$r_s = r_f + (r_m - r_f)\,\beta$

r_s= security or asset

r_f= risk-free rate of interest

r_m= market return

β= beta coefficient

Calculating Beta. Financial professionals estimate beta by using historical stock return data and historical market return data from a specified period that typically ranges between two and five years (Cenesizoglu et al., 2016). Depending on the sample period and type of beta estimation, financial managers use daily, weekly, or monthly historical returns in calculations (Cenesizoglu et al., 2016). The market itself is considered to have a beta of 1.0. The most commonly used U.S. stock market indicators include the National Association of Securities Dealers Automated Quotations (NASDAQ), the Dow Jones Industrial Average (DJIA), and the S&P 500 Index (Bilinski & Lyssimachou, 2014).

For an individual security, a beta of 1.0 indicates that it will be expected to move consistently with the overall market. Hence, if the market is expected to rise by 2% over a certain period, the security will also be expected to rise by 2% over that same period. A beta of less than 1.0 indicates a security less volatile than the overall market, while a beta greater than 1.0 indicates a security more volatile than the overall market. For instance, utility companies typically have a beta of less than 1.0, while high-tech companies have a beta greater than 1.0. A stock with a beta of .75 indicates the stock is 25% less volatile than the overall market. A stock with a beta of 1.2 indicates the stock is 20% more volatile than the overall market.

Estimating beta is as important as understanding the results. Researchers have found inconsistencies with beta estimations depending on the period used to calculate systematic risk. Cenesizoglu et al. (2016) conducted research to determine the most accurate time interval scale for calculating beta forecasts. Cederburgh and O'Doherty (2016) also found that beta varies over time and produces mixed return results. Hong and Sraer (2016) evaluated speculative pricing since beta did not capture systematic risk, while other researchers investigated option-implied betas that are considered an alternative to the more common beta estimations (Baule, Korn, & SaBning, 2016). Hollstein and Prokopczuk (2016) highlighted how much of the earlier research (Baker et al., 2011; Bilinski & Lyssimachou, 2014) had adopted Fama and Macbeth's (1973) two-step linear regressions to calculate beta estimates of monthly returns over a five-year period. Cenesizoglu, Liu, Reeves, and Wu (2016) claim that the most widely used method of forecasting beta remains as Fama and Macbeth's (1973) regression. Despite the plethora of literature concerning the CAPM and beta, no consensus has been reached on whether beta is a suitable measure of risk.

Discussion of relationships between theories and variables. The theoretical framework for this study tested whether a relationship between beta and average monthly returns from the S&P 100 compared to the benchmark. This study was different in that the stocks used are considered blue chip large, cap stocks from some of the largest companies in the United States. To test if a relationship existed, the researcher used the independent variable, expected returns, and dependent variable, actual returns. Mitigating variables included beta category and industry sector.

Summary of the conceptual framework. Based on prior literature regarding beta and expected returns, it is assumed beta and returns are inversely related. The literature indicated the beta anomaly could be explained by including the size of a firm or book ratio. Finally, based on prior literature indicating the assumptions of beta were flawed lead the researcher to believe risk for an investment strategy could be over/under stated.

Definition of Terms

The following terms and definitions are critical to understanding the concepts in this dissertation.

Beta: A measure for systematic risk, indicating the volatility of an asset compared to the volatility of the overall market (Bollerslev, Li, & Todorov, 2016).

Capital Asset Pricing Model (CAPM): The CAPM is a model used to explain the relationship between systematic risk and expected returns of an asset (Dempsey, 2013).

Systematic risk: Risk factors that affect returns of comparable investments and cannot be diversified out of a portfolio (Kadan, Liu, & Liu, 2016).

Unsystematic risk: Risk factors associated with an individual security that can be diversified out of a portfolio (Kadan, Liu, & Liu, 2016).

Assumptions, Limitations, Delimitations

Assumptions. Conceptually, the CAPM has intrinsic assumptions associated with the overall model, such as investors are risk-averse, they retain stocks for one holding period, and all available information is widely known. For this study, the researcher assumed there was a linear correlation between beta and expected returns and that beta was conditional on the information available. The researcher assumed integrity and quality of the data available on the Yahoo! Finance.com website. This source of secondary data is widely considered to be accurate and reliable (Bilinski & Lyssimachou, 2014). If beta estimates were not accurate, the miscalculation would result in an error-in-variables (EIV) (Ahn & Gadarowski, 2004). Jagannathan and Wang (1996) concluded beta and market risk vary over time. The present research builds upon the work of earlier researchers who assumed beta and returns vary over time.

The researcher used historical data from Yahoo! Finance, a publicly available database, to compile actual returns during the period within the scope of this study. The data is readily verifiable and reproducible through multiple public sources and is assumed accurate and reliable. The researcher used companies listed on the S&P 100 as the sampling frame for selecting participant records of historical returns due to the assumption those companies are the most established out of the S&P 500.

Limitations. The primary limitation of the current research is the relative restricted time frame of 2010 through 2018 from which monthly returns of common stocks from the S&P 100 were gathered for part of the investigation. Beta and monthly returns vary over time and that produces sample variability. Groenewold and Fraser (2000) recommended a five-year period of beta and returns be used when researching beta fluctuations and its relationship to returns. Fama and Macbeth's (1973) model was developed based on an analysis of five-year periods over forty-two years (1926-1968). Fama and MacBeth used a longer time horizon to account for pre and post-World War II anomalies.

The researcher will use a five-year time horizon for common stocks from 2012 through 2016, to capture returns after the financial crisis began in 2008-2009. These returns are for organizations listed on the New York Stock Exchange (NYSE) but limited to organizations from the S&P 100. Therefore, the five-year horizon will render the results vulnerable to systematic error due to the limited number of years. The researcher will rely on the traditional method of beta estimates by reviewing the monthly returns of S&P 100 common stocks on the NYSE over a five-year period, as opposed to the traditional method of selecting a particular industry.

Delimitations. The boundaries delineated in the research are limited to five years of monthly returns for common stocks from 2010 through 2018. To develop an understanding of the relationship between beta (risk) and actual returns during that period, participating stocks will be selected from the S&P 100 publicly traded on the NYSE. Each company in the S&P 100 are large and established businesses within the S&P 500. The researcher will select sample participant companies to limit the amount of data points and enhance manageability. However, this study could be replicated with a larger population such as the S&P 500 or a more exhaustive review of all common stocks on the NYSE. The researcher has chosen to study the beta component of the CAPM, because the literature was not clear on whether beta was a suitable risk measure. Since the other components of the CAPM (risk-free rate and the expected rate of return of the market) do not directly influence the beta component, they will not be included as part of the statistical analysis.

The researcher will address a gap in the literature by examining the relationship between beta and return in a relatively small sample size. The literature focuses on monthly returns over larger time spans leading up to the latest financial crisis in 2008; however, research has diminished since the economic recovery to the present day. Black (1993, p.1) suggested the "sample period effect" was responsible for differences in the findings of earlier research (Banz, 1981; Fama & French, 1992). Black (1993) indicated that researchers typically utilize data gathered over decades to provide accurate future expected returns. However, future returns are outside the scope of this study, as the researcher will focus on historical returns to determine if beta captured systematic risk in stock returns. The researcher will use a smaller data set to understand the relationship between beta and historical returns, and to determine if beta captures risk.

Significance of the Study

Reduction of Gaps. Given the significant amount of earlier research, Benson and Faff (2013) claimed that beta was an inadequate indicator of risk when describing variation in market returns. Addressing the existing gap in the literature complements the significance of the current research on whether beta is a suitable measure of risk and for predicting returns. Beta can have a direct impact on an organization's stock price, which was of significance to business leaders and investors (Benson & Faff, 2013). Bilinski and Lyssimachou (2014) posited the accounting and financial literature was insufficient in determining whether beta was a logical measure of risk.

They concluded that beta and the stock returns have a linear relationship, but that more research was needed to verify if ordinary least squares regressions (OLS) tend to move beta closer to zero (Bilinski & Lyssimachou, 2014)

Sanghi and Bansal (2014) noted that beta differences between time intervals created opportunity for future research regarding beta as a risk measure. Messis and Zapranis (2015) identified the significance and importance that beta played in the risk/return relationship and varying beta estimations created problems in using beta as a risk proxy. This research may help fill the gaps and expand on the existing literature as to the appropriate measure of risk for the CAPM.

Implications for Biblical Integration. Van Duzer (2010) stated that Christians have a calling to be stewards of God's creation. God expects all Christians to play a role in being good stewards to His creation and ensure that talents and gifts are used for the betterment of society. God wants humans to flourish and cultivate a deeper relationship with Him. Mitigating risk to accumulate profit is not the underlining idea in sustaining God's creation but accumulating profit to fund the charity of God is the calling of for Christians in business. Christians have a responsibility, through service to the community, to ensure the greater good of God's creation (Van Duzer, 2010). God does not want His human creation to keep talents and gifts only for selfish benefit, but to share their gift with the community. Hardy (1990) implied that Christian's have concerns with their vocation and how that connects with their faith. God calls His followers to serve each other, manifested in vocation or work (Hardy, 1990). Hardy held that work itself was a divine vocation, which joins Van Duzer's concept of meaningful work to allow communities to flourish. Nowhere else are these ideas more evident than in accounting and finance.

Accounting and finance provide a framework by which organizations can use their God given resources to allow their communities to flourish. An organization's customers and employees are the very basis for a company's existence and overall profit was the opportunity to extend God's creation (Van Duzer, 2010). This idea that accounting and finance are the basis to extend God's creation does not come without pitfalls. Humankind lives in a broken society and recent scandals involving malfeasance with corporate accounting and finance have focused attention on the importance of business leaders adhering to responsible accounting practices. This study adds to existing literature as to whether beta is a suitable measure of risk and will help business leaders to become better stewards of God's resources by gaining a greater understanding of beta.

Relationship to Field of Study. When investing resources, effective risk management is a crucial element for business leaders and investors to enable them to calculate the proper risk measures. The CAPM and beta are the fabric of risk intervention used throughout the field of accounting and finance (Bilinski & Lyssimachou, 2014). Cultivating a deeper understanding and contributing to the research on how beta measurements correlate to stock returns is an important issue for accounting and finance practitioners. The next section provides a review of the pertinent literature related to MPT and the evolution of the CAPM and beta risk.

Summary of the significance of the study. Beta, as a risk indicator, continued to be an opportunity in finance and accounting research. The study will reduce gaps in the current literature by determining if a relationship existed between beta and S&P 100 stocks. To date there has not been a study to link average monthly returns from large index stocks in the S&P 100 and beta. This study also fulfills God's calling for Christians to be good stewards of His creation by measuring the difference and association of beta and average monthly returns. Beta and average monthly returns are linked to the accounting and financial field of study as the CAPM is still widely used for investment strategy.

A Review of the Professional and Academic Literature

This literature review discusses and synthesizes the seminal and contemporary literature concerning Modern Portfolio Theory (MPT), Sharpe's (1964) Capital Asset Pricing Model (CAPM) and related concepts and variables. This literature review focuses on the more frequently cited concepts in finance, which causally relates to the problem statement as to whether beta is a suitable risk measure for the CAPM. Anchoring the literature review are four major sections, which include MPT, CAPM, Limitations of the CAPM and Beta Risk Indicator, and CAPM Alternatives and Variations, which include an accounting-based risk model and additional variables shown to influence the relationship between risk and return.

Modern Portfolio Theory (MPT). Markowitz' (1952) seminal work on MPT emphasized the benefits of diversifying risk by combining or pooling assets to minimize risk and maximize returns (Klein, Daza, & Mead, 2013). Diversification is the process of adding multiple securities to a portfolio to minimize overall risk, which in turn reduces an investor's loss (Mayo, 2011). The relationship between systematic risk and the overall market is reciprocal so that if the market rises, individual securities will rise as well (Mayo, 2011). In short, using diversification strategies to limit risk would then allow investors to earn higher returns as the market rises.

Markowitz's (1952) Modern Portfolio Theory, also known as the Mean-Variance Model, defined how investors would choose "mean-efficient" portfolios to minimize risk and to maximize returns. Markowitz proposed the assembly of different stocks to diversify the portfolio, so the expected return was greater than the expected risk. The Markowitz Model combined different securities to diversify and minimize overall portfolio risk (Lee, Cheng, & Chong, 2016). By adopting this model, an investor could minimize exposure to risk by diversifying the portfolio and in turn maximize their returns (Markowitz, 1952). The developments of portfolio theories have sought to minimize risk by using statistical analysis to determine a risk/return relationship (Lee et al., 2016). Although MPT has withstood the test of time among academics and practitioners, the model does little to validate whether beta is a reliable indicator of risk but assumes it is (Mayo, 2011).

Maximizing investor satisfaction, or utility, is the purpose of diversifying portfolios to minimize risk. Risk is the uncertainty that investors assume when investing in capital markets. There are two types of risk: systematic risk and unsystematic risk. Unsystematic risk is considered risk that is unique to an asset and diversified out of a portfolio while systematic risk is not diversifiable and influences the returns of all market securities and pricing (Mayo, 2011). Traditionally, research efforts have focused on efficient markets and systematic risk because of its impact on market returns.

The Capital Asset Pricing Model (CAPM). Recognizing that MPT offered only partial explanations for risk and market behavior, Sharpe (1964) developed the CAPM to account for the role of risk in stock returns. Fama and French (2004) described Sharpe's seminal thinking on the CAPM as an algebraic function that predicts the relationship between risk and expected return. Kim and Kim (2016) support the CAPM as an extension of MPT and an efficient means of calculating risk.

While the original and basic principles and practices are evident today, asset-pricing methodologies and risk calculations have been refined over the past seventy years through the adoption of various assumptions (Blitz et al., 2014). The underlying assumptions of the CAPM are: (1) financial markets are efficient, (2) investors seek arbitrage opportunities to exploit, and (3) investors are rational (Blitz et al., 2014). At the heart of asset pricing, investors seek to identify risk, which confirms the notion that investors seek arbitrage but does discount the idea that all investors are rational and objective (Blitz et al., 2014).

The CAPM utilizes objective statistical analysis to measure the linear regression between beta and stock returns (Schroder et al., 2014). In other words, when investment managers use the CAPM to predict future returns, based on historical analysis, predictions identify how the reported value of risk contributed to an actual expected return. The most recognized systematic risk measure associated with the CAPM is beta, which is the foundation for determining the risk premium of the CAPM. Systematic risk, denoted by beta, is the risk that investors cannot remove from a stock or portfolio by adding a broader range of stock assets (Sanghi & Bansal, 2014).

The formula to calculate the CAPM, displayed below, is the simple formula used by practitioners. A security or asset notated by r_s and equals the risk-free rate of interest (r_f) plus beta (β), multiplied by the market return (r_m) and risk-free rate (r_f).

$$r_s = r_f + (r_m - r_f)\,\beta$$

The security market line (SML) that represents the expected return of a stock relative to systematic risk graphically represents the calculation of the CAPM. The x-axis represents the systematic risk (beta) and the y-axis represents the expected market return. Figure 1 below, presents an example of a SML graph with an upward slope to the right indicating that an investor taking a greater risk would expect a higher return.

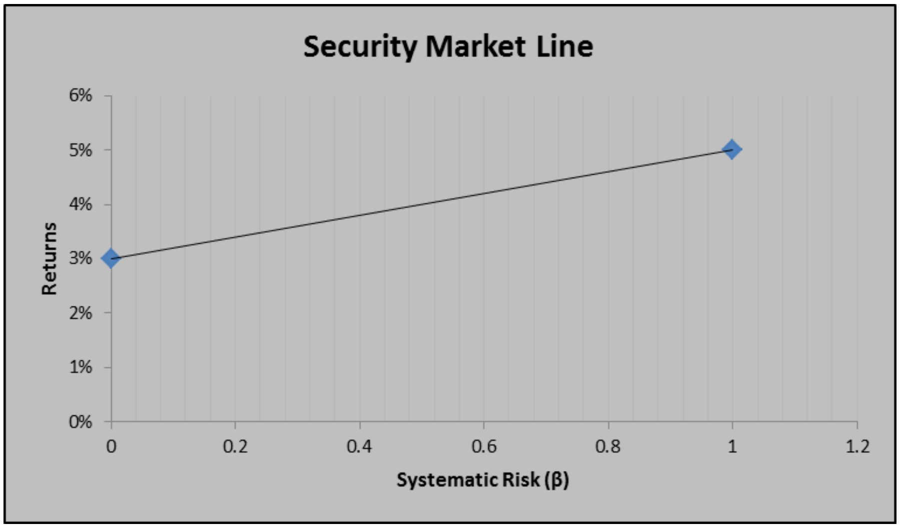


Figure 1. Example of Security Market Line (SML) revealing a positive linear relationship between systematic risk (beta) and stock or market returns.

The graph below (Figure 2) depicts the low-beta anomaly with the SML featuring a downward slope to the right, indicating that higher risk produced lower returns. The slope of the line in Figure 2 is of interest because of the so-called low-beta anomaly, because various low-beta stocks have produced higher returns than high-beta stocks and disagree with the CAPM (Hong & Sraer, 2016).

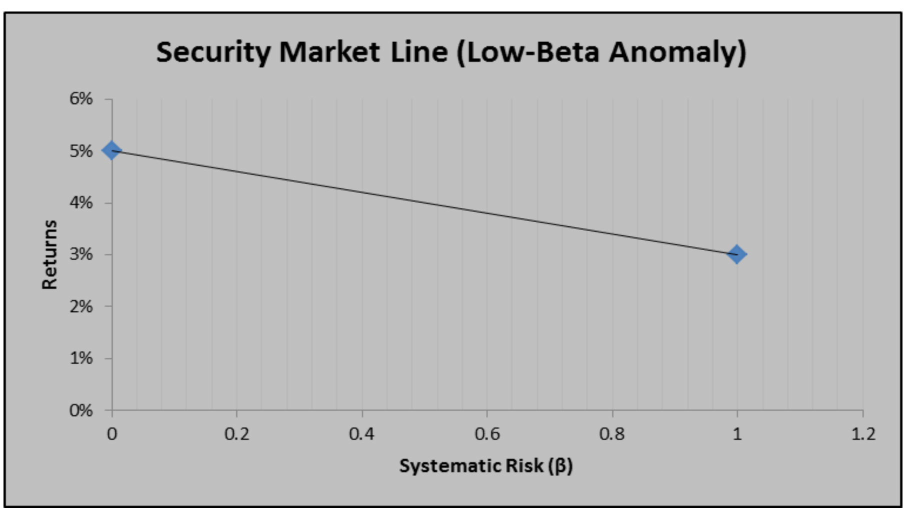


Figure 2. Security Market Line revealing a low-beta anomaly.

Figure 3, below, reveals a flat correlation between beta and return. The flat slope in Figure 3 indicates that a high-beta stock would generate the same returns as a low-beta stock. This contradicts the CAPM assumptions that high beta stocks or high risk will reward investors with higher stock returns.

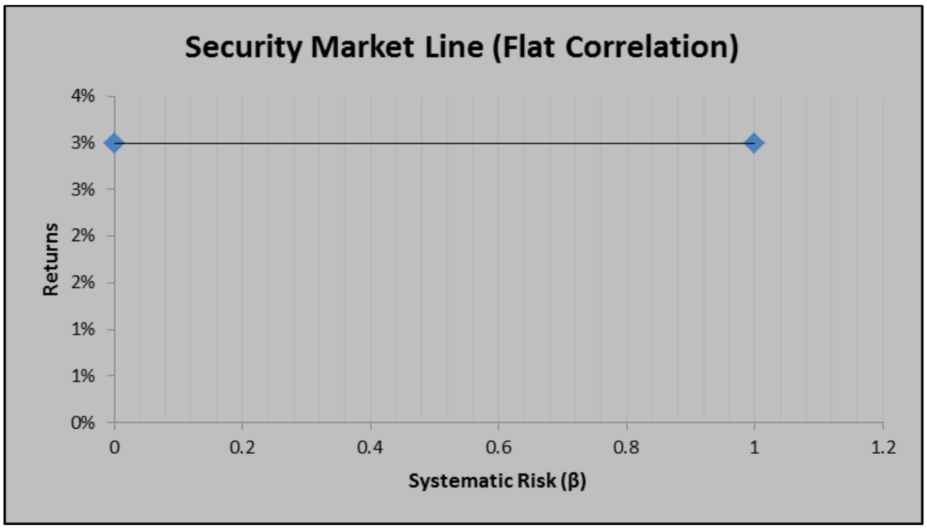


Figure 3. Security Market Line revealing a flat or no correlation between beta and return.

The development of the CAPM is considered by academics and practitioners to be a significant financial and economical achievement (Dawson, 2015). However, the CAPM is dependent upon use of beta, which has been the target of considerable criticism for not identifying risk properly. Indeed, Sharpe's (1964) seminal thinking and proposal for asset pricing, was quickly challenged by contemporary researchers who questioned whether beta was an accurate measure of risk for the CAPM (Hollstein & Prokopczuk, 2016).

As stock information became more readily available, the issue of lower risk stocks outperforming higher risk stocks, as measured by stock returns, inspired much debate to counteract the CAPM assumption that beta was an accurate measure of risk (Dawson, 2015). The inconsistency of lower risk stocks having higher returns was termed the low-beta anomaly.

Beta as a risk measure. There is continuing debate among scholars concerning the suitability of beta to capture systematic risk along with evolving asset pricing models further delineate the need to a new risk premium indicator. While the Efficient Market Hypothesis (EMH), MPT, and the CAPM have contributed to the foundation for financial applications to measure risk and return, these methodologies have also created dissent in the academic community regarding the appropriate method to capture risk and return for the CAPM.

Beta gives the investor a measure of volatility for a stock and the inherent systematic risk involved (Sanghi & Bansal, 2014). Beta can represent varying values, which are either negative, zero, between zero and one, one, and greater than one (Sanghi & Bansal, 2014). Return intervals are of importance when estimating beta, particularly in emerging markets, which tend to have higher volatility.

Researchers have not reached a consensus on the credibility of beta to capture systematic risk. Perkovic (2011) indicated 30 years of academic debate had not solved the validity of beta as a risk measure and concluded that beta is not a suitable risk measure for underdeveloped markets. Testing of the two-pass regression model against 15 stocks listed on the Croatian stock market from 2005 until 2009 resulted with bias due to the smaller sample size of the Croatian stock market (Perkovic, 2011). The smaller stock index explained the reason beta did not capture systematic risk.

Beta estimation techniques are crucial when implying systematic risk to asset pricing models (Hollstein & Prokopczuk, 2016). A broad analysis of varying beta estimation techniques, such has historical, time series, and option-implied beta, which uncovered a correlation between historical beta estimations outperforming time series or option-implied beta (Hollstein & Prokopczuk, 2016). Option-implied betas had seen promising results over the past decade because the estimation included forward-looking stock distributions (Hollstein & Prokopczuk, 2016). Implied-option betas had a major flaw due to the fact the entire market index had to be utilized as opposed to historical or time series betas. Option-implied beta were overall more stable but required an entire index and only those stocks listed on the index (Hollstein & Prokopczuk, 2016).

Baule, Korn, and SaBning (2016) found beta estimations using option-implied techniques had far better results compared with short time horizon results. Implied betas performed better than historical betas when higher option activity was present, which is an underlying signal of a large move in stock value (Baule et al., 2016). Homogenous blue-chip stocks from the Dow Jones Industrial Average (DJIA) were used which created a strong statistical significance for implied betas compared to historical betas (Baule et al., 2016). Implied betas forward looking estimations provided greater positive results than historical betas. While other beta estimation methods have shown promise, researchers could not settle on the appropriate beta calculation, which resulted in further beta estimation theories.

Another such beta estimation technique is conditional beta, which used a dynamic conditional beta method to explain stock returns, has also showed promise (Xiao, 2016). Xiao (2016) and Morelli (2011) both concluded beta was a suitable risk measure, but only when excess returns were recognized. Morelli used an autoregressive conditionally heteroscedastic (ARCH)/generalized autoregressive conditionally heteroscedastic (GARCH) statistical model to properly account for time series data of the United Kingdom stock exchange.

Beta is a suitable risk measure if excessive returns were present during the testing period (Morelli, 2011). Xiao (2016) followed the same methodology; testing the ARCH/GARCH model for time series data on the United States stock market using stock returns from the Russell 3000 index. Similar to Morelli (2011), Xiao found beta did account for returns in those stocks so long as excessive returns were recognized. Both researchers found beta to have an insignificant relationship with stock returns when excessive returns were not recognized (Morelli, 2011; Xiao, 2016).

Statistical correlation however was not found when using a single-factor model (SFM) with autoregressive betas and with an SFM- GARCH model (Koundouri, Kourogenis, Pittis, & Samartzis, 2016). The SFM with autoregressive betas were unpredictable and clustered around the mean returns, resulting in beta variations that did not properly identify conditional heteroscedasticity (Koundouri et al., 2016). Both the SFM with autoregressive beta and GARCH failed to capture systematic risk in stock returns.

Betting against beta was another strategy developed to explain why investors pooled in mutual funds do not leverage against higher risk (Frazzini & Pedersen, 2014). Mutual funds categorized by risk, such that a normal diversification compared to an aggressive diversification, could allow investors to choose normal mutual funds diversification and achieve higher returns compared to aggressive funds (Frazzini & Pedersen, 2014). Normally diversified funds tend to spread stocks and bonds in the portfolio, with a slight tilt to stocks that have lower beta stocks to diversify the risk of high beta stocks (Frazzini & Pedersen, 2014).

An aggressive fund is heavily tilted toward stocks with upwards of 90% stocks and would capture higher returns due to the greater volatility would mean the aggressive fund required less low beta stocks (Frazzini & Pedersen, 2014). If normal funds were efficient, they would have greater returns over time compared to the aggressive fund (Frazzini & Pedersen, 2014). A strategy of Betting Against Beta (BAB) by short selling high beta stocks and buying low beta stocks to leverage up, predicted a positive average return between high and low beta stocks (Frazzini & Pedersen, 2014).

Cederburg and O'Doherty (2016) added to the BAB discussion by examining the performance of beta while considering the predictable time-series variation of portfolio betas. They argued the beta anomaly of low beta stocks outperforming high beta stocks over time continued to damage the CAPM and the explanation of market risk. If investors do not receive a higher reward for the higher risk, the CAPM should be rejected (Cederburg & O'Doherty, 2016). The beta anomaly was in fact less prevalent when stock performance was measured against portfolio-sorted betas and the CAPM did reward investors when portfolios were sorted based on beta.

Identifying the difference between asset pricing theories that captured different conclusions depended on a continuous or discontinuous market beta. The variation in continuous or discontinuous market betas classified as a rough beta (Bollerslev, Li, & Todorov, 2016). Rough betas, which are intraday price discontinuities and overnight close-to-open returns, were statistically significant and more accurately reflected in the relation with systematic risk (Bollerslev et al., 2016).

Stock returns as a variable. Investors are assumed risk averse and attempt to minimize risk while simultaneously maximizing returns of a stock, predicated by the market return. Market prices move in accordance with all available information, which leads to an intrinsic value reflected in the security price (Fama, 1965). This means that security prices randomly move in accordance with the available information, making accurate future predictions based on historical returns impossible (Fama, 1965).

Investors use market returns in the CAPM by regressing against security returns to measure the volatility of an individual security. Sharpe (1964) posited that the basis of the CAPM is that stock returns are proportionate to market returns as a whole. Market returns are typically used as the baseline to measure against individual stock returns. Berk and Van Binsbergen (2017) reported that the Standard and Poor's (S&P) 500 index is the most commonly used benchmark for market returns in most scholarly studies. Other indexes can be used as a benchmark, but most investors use the S&P 500 due to the amount of large cap companies, which represent the overall stock market (Natter, 2018). Market returns, as they pertain to the CAPM, are the gains or losses of a stock for a specific market.

Beta anomaly. As early as the 1970's, researchers observed low-beta stocks outperformed high-beta stocks with regard to returns (Blitz, 2014). Black, Jensen, and Scholes (1972), Fama and MacBeth (1973) and Haugen and Heins (1975) were the first to recognize the low-beta anomaly and highlight the inconsistencies of beta to capture risk. This inconsistency for market returns was termed the low-beta anomaly.

The low-beta anomaly proved counter intuitive which in turn also lead to researchers questioning the long-promoted belief of the role of pure rationality in investment decision-making behaviors. The notion that investors with long investment horizons could achieve larger market returns by using a broad low-beta portfolio created controversy as to the efficiency of the CAPM (Bilinski & Lyssimachou, 2014). The assumption from investors that high-beta stocks outperformed low-beta stocks resulted in more researchers looking to explain the low-beta anomaly. Some models are predictive in nature and seek to account for risk when the assumptions of the CAPM have not been met. Alternative theories and models discussed below include the EMH (Fama, 1970), the Two-Factor Model (Fama & MacBeth, 1973), and the Three-Factor Model (Fama & French, 1992) based on ordinary leased square regressions.

The hypothesis for the CAPM was based on risky stocks providing a higher expected return than less risky stocks and tends to have better performance over a longer horizon (Bilinski & Lyssimachou, 2014). Sharpe (1964) found beta explained the cross-section of stock returns, but the limited scope of stocks evaluated was not robust enough to signify the CAPM legitimacy. Evidence from more recent returns showed no correlation or statistical significance between beta risk and stock returns (Bilinski & Lyssimachou, 2014).

Bilinski and Lyssimachou (2014) assessed the CAPM beta as a control metric in accounting and financial research to capture stock returns, using data from 1975 through 2005. Using logistic regressions for large positive returns and large negative returns, market betas for both regressions produced evidence that beta captured risk in stock returns and focused their attention to the cross-sectional tail clusters for both regression tests. The findings of their study confirmed that high-beta stocks are more risky and low-beta stocks are less risky (Bilinski & Lyssimachou, 2014).

Efficient Market Hypothesis (EMH). The Efficient Market Hypothesis (EMH) has been at the foundation of asset pricing theories for the past sixty years (Fakhry, 2016). Fama's (1970) seminal work on the EMH established the notion that asset prices reflect all available information making it impossible for investors to beat the market. Fama explained that the conditions for market efficiency were not frictionless. The conditions for efficiency were no transactional costs for trading, information to all market participants was costless, and all agree on the implications of current information available established current and future distributed prices of each stock (Fama, 1970). The notion that markets would move in complete agreement with the EMH was not practical in actual market behavior but provided indicators of market inefficacy. Fama believed that those factors of market inefficiency could be used to measure their effects on stock pricing.

The EMH association with the assumptions that a large number of participants compete in the financial markets, information is readily available, and transaction costs are relatively small is similar to the CAPM assumptions regarding market efficiency (Fakhry, 2016). The EMH has been a prominent and influential theory in the financial literature although there is consensus that investors are less rational than proposed and that rationality can vary simply depending on the prevailing circumstances of any given day. These ideas and others have led to a broad perspective of how rational investors interact with capital markets and have spawned a new area of study, termed behavioral finance, in an effort to understand how individuals rationalize financial-related decisions (Kilger, van den Assem, & Zwinkels, 2014). Fama (1970) proposed three forms of the EMH, including weak form, semi-strong form, and strong form, which are described in the following sections.

Weak Form EMH. Weak form EMH implies that the market is efficient because it reflects all historical market information (Fama, 1970). Under weak form EMH, historical, technical, and descriptive information concerning pricing should provide little or no predictive power for estimating returns (Degutis & Novickyte, 2014). Earlier researchers found stock prices and expected returns were random in explaining stock price movement. This random movement was explicit in the random walk theory, which holds that stock prices have the same distribution and are independent of each other (Fama, 1970). The random movement of stocks means that historical prices or price trends cannot be used to predict future market returns.

Semi-Strong Form EMH. Semi-strong market efficiency implies that the market rapidly reflects all new publicly available information and that fundamental analysis should be of no use in predicting future stock prices (Fama, 1970). Semi-strong form EMH includes the elements of weak form EMH plus public information that might influence an investor's decision-making behaviors such as mergers and acquisitions, bonus payouts, accounting policy adjustments, or dividends and payouts (Degutis & Novickyte, 2014). The semi-strong form may well influence decision-making through cognitive and emotional bias and so this form implies less than optimal rationality despite this being an underlying assumption for this and the CAPM. The semi-strong form also ensures that stock prices reflect all the above listed information and so pricing adjusts rapidly to prohibit excessive profits (Manasseh et al., 2016). Fama (1970) specifically focused on public announcements of annual earnings and stock offerings to highlight the empirical strength of the semi-strong form EMH.

Strong Form EMH. Strong form EMH implies that stock prices reflect all the combined public and private information available to investors (Fama, 1970). Since it includes information that is not readily available to the public, strong form EMH has also been associated with insider trading and the illegal practice of investors trading stocks to personal advantage by using confidential market and risk information to influence returns (Degutis & Novickyte, 2014). With that said, while strong form EMH incorporates all information into the stock price meaning it still does not provide an advantage of realizing excess returns because all information is known and in the stock price.

Two-Factor Model. Fama and MacBeth (1973) focused on the two-factor model of ordinary least squared regressions to investigate whether the stock market is as efficient as widely accepted and whether investors are risk averse. These researchers calculated risk as the measure of total dispersion in each security distribution and considered beta to be a condition of risk in an asset allocation which supports the CAPM's assumption of risk (Fama & MacBeth, 1973). The findings supported the two-factor model as a method to measure risk for market returns; however, the two-factor model could not account for other mediating or moderating variables, such as firm size or book-to-market ratios. Fama and French's (1992) research is cited today as a reliable method to evaluate the CAPM risk model and has been instrumental in influencing contemporary thinking and research on the matter.

Fama and French (1992) suggested that the CAPM not only laid the foundation for understanding the relationship between risk and return but also provided the framework for building more refined models involving additional variables to the regression equation. One such refined model is The Three-Factor Model in which researchers add the variables of firm size and book-to-market ratios to show their effect on the sensitivity to beta. As more researchers focused on the CAPM and larger amounts of market information became more widely available, the relationship between beta and the average return was found to be moderated or mediated by additional variables not previous accounted for in early research (Fama & French, 1992). Fama and French found operating and financial leverage have very few interactions and recommended further research into the relationship between operating and financial leverage on equity risk measures. In other words, the relationship between CAPM's beta security indicator and expected market returns became flat and not representative of the model's expectations.

Fama and French (1992) conducted empirical research on the cross-section of expected stock returns and questioned whether beta accurately captures risk versus return of market securities. They concluded that firm size and book-to-market ratios captures true risk better than the beta value. While accepting the inherent flaws in beta's accuracy as a measure of systematic risk, Fama and French found that the relationship between risk and return for the period 1963 to1990 eroded or was flat compared to the earlier years. They also found that beta was not correlated with market returns as originally predicated, but that size and book-to-market was a better indicator of risk when compared to overall market returns.

Fama and French (1992) found that market returns from 1941 to 1990 had a weak correlation with market returns when compared to beta. The cross-section of expected returns had a stronger correlation when measured against a firm's size and book-to-market equity. Fama and French used those two variables (size and book-to-market equity) due to the ease of readily available information. The results suggested that when a variation of beta is unrelated to firm size, the average expected return when compared with market beta is flat.

Three-Factor Model. Based on the findings of the book-to-market and firm size effects on the relationship between beta and stock returns, Fama and French (1996) proposed a Three-Factor Model to explain market risk better than the CAPM alone. The Three-Factor Model is similar to the CAPM in that it includes beta as well as including firm size and the book-to-market ratio. Firm size is essentially the market capitalization, while the book-to-market ratio is the value of an organization relative to a stock portfolio (Sharma & Mehta, 2013).

Even after the evidence suggests that the Three-Factor Model is a more accurate risk indicator, Fama and French (2004) contended that the CAPM is flawed by further variables over and above beta with the greatest influence caused by firm size. The Three-Factor Model is better suited to account for varying risk factors but falls short of estimating beta through multiple periods (Dempsey, 2013).

Accounting Based Risk Theories. Scholars and practitioners sought to increase the robust nature of the CAPM by including new methodologies. Researchers identified other factors for systematic risk. One such method added, was accounting-based risk measures (ABRM) to address previously established risk measures found in accounting (Mensah, 1992). Seminal researchers Hamada (1972) and Rubinstein (1973) considered the influence of market beta as both financial and operational risk factors (Mensah, 1992). To remedy market beta inconsistencies researchers introduced ABRM as an enhancement to the CAPM. To equate systematic risk from accounting-based risk factors, investors would need to equate the impact of systematic risk to a firm's equity.

The total, systematic, and unsystematic risk characteristics of a firm affected the four types of equity and the prevalence of a firm's equity risk was directly tied to financial leverage and operating leverage (Lord, 1996). A firm's financial leverage has a direct relationship with systematic risk and accounting betas linked systematic risk to a firm's profitability (Lord, 1996). While correlations existed between systematic and unsystematic risk with regards to operating leverage and net profit, Lord (1996) determined that equity risk was not robust enough to validate those findings. To link ABRM, researchers would need to develop a rate of return based on accounting risk.

A relationship between quality of accounting information and systematic risk established a link between ABRM and market returns (Xing & Yan, 2018). A review of literature surrounding accounting information quality and the cost of capital provided emperical evidence that poor accounting information affects systematic risk factors (Xing & Yan, 2018). Armstrong, Banerjee, and Corona (2013) explained that a firm's cost of capital is directly dependent on the firm's exposure to systematic risk and the quality of accounting information. More specifically, a firm's accounting information can affect investor uncertainty on expected returns, which ties to quality of accouting information (Armstrong et al., 2013).

A framework using ABRM as an alternative to the CAPM developed a link between fixed cost and variable net cash flows (Toms, 2012). Due to the financial disruptions in 2008 and new standards from the International Financial Reporting Standards (IFRS) Board, questions around the suitability of the CAPM to determine a firm's risk primed the environment for determining if accounting information could replace the need for market risk analysis from market information (Toms, 2012). Toms (2012) proposed using accounting based risk factors to establish an organization's risk for capital budgeting projects as opposed to traditional market information. Using accounting information and principles links risk to expected returns (Penman, 2016). Anomalies in the CAPM are explained by ABRM and an extension to the CAPM when determining discount rates for capital inputs and evaluation of systematic risk (Toms, 2012).

ABRM used risk estimates from revenue and cost behavior weights to assess their impact on the accounting rate of return so that discount factors could predict systematic risk in capital markets (Toms, 2012). Toms (2014) measured the difference between the CAPM and ABRM to determine if ABRM could capture systematic risk as effectively as the CAPM. The main difference in the ABRM is the generated discount factors to manufacture risk-adjusted returns (Toms, 2014). Cross-sectional returns for the CAPM were not evenly distributed, but the combination of the CAPM and ABRM minimized deficiencies found in the CAPM. Another method to explain corporate risk is credit risk. Credit risk has both accounting and market models to establish an organizations credit risk, which in turn is the organization's volatility.

Credit risk was at the center of the financial collapse in 2008, which extended the need for asset pricing models to incorporate other factors to capture systematic risk (Allen, McAleer, Powell, & Singh, 2016). While the ABRM can transform data into a discount rate, which is used to estimate an organization's overall risk, Trujillo-Ponce, Samaniego-Medina, and Cardone-Riportella (2014) looked at whether accounting models, market models, or a combination of both, could identify credit risk to capture volatility. Establishing systematic business risk through cash flow analysis yielded the starting point for ABRM calculations, but financial ratios are used to measure credit risk (Trujillo-Ponce et al., 2014).

Hill and Stone (1980) expanded on the empirical and theoretical framework of accounting-based and market-based risk. The understanding that investors need accurate information on systematic risk to make informed decisions was needed in many areas of business. Hope, Hu, and Lu (2016) highlighted the need for greater disclosure when organizations report risk factors in their financial filings. Systematic risk was defined as a broad, but complex, category of risk measures that affect the aggregate of market returns (Kadan, Liu, & Liu, 2016).

Hill and Stone (1980, p. 2) found that previous risk measures were "crude" and needed further research to validate the association between risk and risk measures and argued that beta analysis of *ex ante* returns was the standard for evaluating market returns. Using accounting data to develop the cost of capital is contrasted for ABRM, compared to the CAPM, which uses stock market data to determine the cost of equity. Accessing stock market data compared to financial data is relatively the same. Beta factors are readily reported on financial websites, but book-to-market measurements and firm size are more difficult to ascertain (Toms, 2012).

Er and Kaya (2012) found a close relationship between CAPM and accounting beta in Turkish markets, compared to other studies that primarily focused on developed markets. Developing markets tend to have fewer financial regulations making it harder to use financial records from companies not publicly traded to yield a risk beta (Er & Kaya, 2012). The CAPM is only used on publicly traded companies and while the results indicated a relationship between ABRM and beta for private companies it did not clearly establish a correlation (Er & Kaya, 2012). The results were varied due to the limited data and the sample period was short, which did not invalidate the CAPM for developing economies (Er & Kaya, 2012).

While researchers have found challenges using the CAPM in developing markets, the CAPM is still a good measure to extrapolate risk from pooled investments (Bilinski & Lyssimachou, 2014). The CAPM does require increased scrutiny regarding market betas and whether risk is properly captured to valuate stock returns (Bilinski & Lyssimachou, 2014). Returns from high beta stocks tend to cluster in the tails of the cross-sectional distribution for large positive and large negative market returns, which does capture risk but still does not explain how low-beta stocks outperform high-beta stocks (Bilinski & Lyssimachou, 2014).

Limitations of the CAPM and Beta Risk Indicator. Banz (1981) introduced the phrase size effect to reflect how market equity and the cross-sectional nature of observed returns are skewed due to firm size. It was noted that the CAPM had mispriced organizations for over forty years. The size effect indicated smaller organizations had higher risk adjusted returns compared to larger organizations (Banz, 1981). At the time, it was unknown whether small firm size was a proxy to risk adjusted returns, but it was clear that medium to large organizations had slight differences with returns (Banz, 1981). This was a precursor to Fama and French’s (2004) argument that firm size exerted the greatest amount of influence on the strength of the relationship between beta and stock returns.

While the CAPM is an attractive and simple means for evaluating risk, it has a poor record of explaining the relationship between risk and reward of stocks (Fama & French, 2004). Even with the uncertainty, Fama and French (2004) conceded that they would continue to teach CAPM as an introductory building block to stock risk valuation, but that the theory invalidates itself due to empirical results, suggesting the application is flawed when other risk measures such as firm size are included in beta evaluation. This rationale laid the groundwork for other researchers to examine a more in-depth analysis into the CAPM's viability and to produce new strategies for explaining risk.

CAPM and irrationality. Dempsey (2013) encouraged debate around the CAPM and concluded that it was a failure in finance and economic study because modern finance research was flawed. Academics accept the premise that markets are rational when in fact, markets are not rational and they do not self-correct (Dempsey, 2013). Dempsey (2013) rejected market rationality and urged investors to return to pre-CAPM portfolio adjustments, mainly because the market responds to good news or bad news perpetuated by the degree of optimism or pessimism.

Cai, Clacher, and Keasey (2013) agreed that imposing a rational model on an irrational market does not explain the insensitivity of interval scales or tools to measure beta over time as accurate or efficient means of predicting returns. Fama and French (2004) suggested that limiting portfolio choice to only U.S. stocks could be at the root of the limitations of the CAPM although the rationale for this proposition is unclear. Some researchers have proposed that studies focus more on the behavioral aspects involved in the investor decision making models (Cai et al., 2013) while others support Dempsey's argument that the CAPM should form the basis of data mining to identify additional factors and models that influence and explain the risk-return relationship (Moosa, 2013).

Behavioral approach to risk. Moosa (2013) argued that academic research should invest in developing alternative theories and models to the CAPM especially given the concerns surrounding the beta's predictive ability. Alternative concepts to explain the relationship between risk and return would be better developed on a foundation or discipline more closely related to the behavioral sciences so light could be shed on the cognitive processes and emotional reactions investors experience when making decisions to invest in each stock (Moosa, 2013). Ultimately, Moosa criticized research based on circuitous hypothesizing and theorizing despite the evidence that beta, and methods of observation, are flawed.

CAPM weaknesses. Bornholt (2013) supported Moosa's (2013) position that three major flaws weaken the CAPM: beta anomalies, value anomalies, and momentum anomalies. The beta anomaly states that beta does not capture the return of high and low beta stocks accurately (Bornholt, 2013). Book-to-market ratios create a value anomaly in that a high book-to-market ratio has a higher return than organizations with a low book-to-market ratio (Bornholt, 2013). The momentum anomaly is used to describe an organization that experiences high returns in one six to twelve-month period and tends to have high returns the during the following six to twelve-month period (Bornholt, 2013).

The weakness in beta observed since 1993 has raised questions about the cause of beta flattening and higher returns in modern financial research. Further, the timeline suggests that external factors prevalent at the time might have changed how risk is indicated. Black (1993) claimed that tilting stock portfolios to a low-beta asset allocation could cause the relationship between beta and return to become flatter. When investment managers encourage low-beta investments, considered due to market approximation estimates, those will outperform decision making based risk indicators (Bornholt, 2013).

A call for more financial research and an open discussion regarding the limitations presented in the CAPM was critical to settle the misconception of the data (Johnstone, 2013). Chochola, Huskova, Praskova, and Steinebach (2013) called for more robust statistical testing of CAPM, and alternative models, that would utilize the ordinary least squared regression (OLS) rather than simple or multiple regression analysis.

The widely known assumption that OLS regression has issues with sensitivity, due to time deviations, indicated that researchers should focus on a more robust measure of beta to predict market risk (Chochola et al., 2013). Johnstone (2013) found that many investors, who use the CAPM, or the more recent models of asset pricing, do so because finance and statistics go hand in hand when making financial decisions. Due to the synergies in statistics and finance, asset pricing creates a simple verification but can also create an endless evolution of niche models. The difference in financial models and statistical models is that financial modeling is a new philosophy, whereas statistical modeling is a well-defined discipline (Johnstone, 2013).

Handa, Kothari, and Wasley (1989) used a generalized least squares regression model (GLS), which produced a statistically significant relationship between beta and returns, as opposed to the later methods that used OLS. Benson and Faff (2013) claimed the general importance of utilizing the GLS tends to be overlooked when discussing traditional CAPM and the statistical relationship between beta and returns. General discussions surrounding methodology and analysis have highlighted the increasing difficulties in testing the CAPM regardless of the statistical model (Partington, 2013). Using *ex post* data rather than *ex ante* data along with unobservable asset betas complicates testing (Partington, 2013). Noda, Martelanc, and Kayo (2016) tested the idea of *ex ante* accounting models by using earnings/price risk factors based on the Fama and French Three-Factor Model and found that earnings and price ratios used as a proxy for *ex ante* cost of equity is a better indicator of risk and returns in Brazilian markets.

While arguments against the CAPM continue, it remains the most commonly adopted asset pricing and risk model for investors (Partington, 2013). The core of the CAPM is diversification to limit exposure to risk (Smith & Walsh, 2013). The CAPM was born out of MPT, hence the overwhelming belief that diversification is the foundation of a risk-reward tradeoff for asset pricing. Anchored in the minds and behavior of investors, diversification is the path to utility. Kim and Kim (2016) utilized a volatility function to capture the full dynamic nature of the CAPM and its ability to capture stock volatility. Rather than focusing on the traditional benefits of diversification rooted in the CAPM, Kim and Kim (2016) suggested expanding the model to include assumptions about how volatility can affect or influence the risk-return relationship in the statistical regression analysis.

Risk-return research methodologies: Static versus dynamic. The assumptions of the CAPM have been subject to numerous interpretations and examined using a relaxed methodology (Shih, Chen, Lee, & Chen, 2014). Shih et al. (2014) categorized the last forty years of CAPM research as static CAPM and dynamic CAPM. Static CAPM follows the methodology refined over the years to form a single period CAPM model that also incorporates the mean-variance CAPM (Shih et al., 2014).

Other models, such as the dynamic CAPM, incorporate a more continuous time model to account for investment opportunity and expected returns (Shih et al., 2014). Shih et al. (2014) contended that inter-temporal models are consistent with market efficiency in that inter-temporal models use a continuous timeline as opposed to a single period model. Adrian, Moench, and Shin (2015) investigated the parsimonious dynamic pricing model as a forecasting tool for intermediary leverage theories. The intent of the study was to redirect the discussion around financial frictions and their effects on asset pricing (Adrian et al., 2015).

The notion that financial conduits act in accordance with the average investor is central to pricing risk in an alternative fashion (Adrian et al., 2015). Binh and Jhang (2015) examined the equilibrium model and the effect of unsystematic risk. The assumptions for the CAPM that investors are rational set the stage for the underpinning that systematic risk is the only risk that matters (Binh & Jhang, 2015). The assertion that only systematic risk is important for the CAPM was eroded by recent empirical research that finds idiosyncratic risk can be valued as well as systematic risk (Binh & Jhang, 2015). Existing literature on idiosyncratic, or unsystematic, risk indicates it might play a larger role in asset pricing than first understood. The equilibrium model captured the adapted CAPM's continuous time exchange and established an economy asset-pricing model (Binh & Jhang, 2015). The conditional CAPM is a stochastic method of using time-varying market betas to explain returns based on how far back historical data is gathered for inclusion in the model and analysis (Xia-fie, Zong-Wu, &Yu, 2013).

Influence of International Exchange. Another variation to the CAPM is the consumption CAPM (CCAPM) developed when Stillwagon (2015) found a correlation between CCAPM and expected currency returns. International currency fluctuations are unpredictable and create risk when investing in international and emerging markets and the CCAPM is cyclical in nature, which helps create a positive correlation between the overall economy and the overall returns (Stillwagon, 2015). Using expected returns as opposed to *ex post* returns, continuous periods, and real exchange rates are all important to consider for the CCAPM (Stillwagon, 2015).

Stillwagon concluded that longer periods of looking back and incorporating *ex ante* data could resolve the gap in price to explain higher than anticipated returns in the CCAPM.

Inconsistencies. Criticism of the CAPM is due in large part to the inconsistencies in the assumption of beta estimates and investor holding periods. Statistical errors in beta calculations for past returns are classified as estimate errors. Estimation errors of beta led researchers to compensate for statistical sensitivity to the inaccuracies statistical models can present. Such statistical variability for beta estimation or outlying stock returns distorts the statistical analysis of portfolio risk. These disruptions, termed perturbation, create uncertainty in statistical models and should be treated with care when making overall calculations for the CAPM. Galea and Gimenez (2016) conducted sensitivity analysis of the small disruptions in statistical models used in the CAPM and found that local influence diagnostics could capture outlying stock returns that could distort the statistical significance and performance of the CAPM.

Emerging Markets. The CAPM performs in much the same way in international and emerging markets as it does in the U.S. (Blitz et al., 2014). Volatility also affects the CAPM in international and emerging markets just as it does in the domestic market. This adds weight to the reliability and validity of the model and its underlying assumptions. The basic CAPM assumptions that question the model are categorized as follows: no constraints on leverage and short-selling, investors are risk adverse, there is only one period, information is complete and rational, and markets are perfect (Blitz et al., 2014).

Emerging markets compound the sensitivity of stock returns when calculating the CAPM due to uncertainty, such as political climate or regulatory authority. Galea and Gimenez (2016) documented the perturbations observed in emerging markets by using diagnostic methods to capture frequent risk outliers that distort market returns. Identifying those risk outliers from emerging markets provided a unique opportunity to handle risk outliers in econometric data sets and provide statistical significance for continuing to use the CAPM to estimate risk and return for stock returns or for estimating the cost of capital (Galea & Gimenez, 2016).

Portfolio managers seek to minimize risk while maximizing return but in emerging markets, estimating risk can be challenging. Emerging markets have limited stock choices that render diversification arduous if not impossible (Heymans & Brewer, 2016). Heymans and Brewer (2016) created a mechanism to combat portfolio inefficiencies in emerging markets by using a volatility spillover effect to counterbalance markets with limited portfolio selection. MPT and the CAPM use beta to measure volatility. Using beta estimation for the CAPM or MPT to construct an efficient portfolio in an emerging market can be achieved by continuous rebalancing to eliminate volatility spillover from portfolio to portfolio (Heymans & Brewer, 2016).

Beta can still be effective in emerging markets; however, investors should be cautious when analyzing stock return criteria in emerging markets. Degutis and Novickyte (2014) also noted the challenges of establishing risk premiums for stocks in emerging markets. Inefficiencies in emerging markets and the lack of empirical research have distorted the reality of investor utility. Investors typically see higher volatility in emerging markets, which makes those markets more inefficient.

CAPM Alternatives and Variations. As previously mentioned, the CAPM has not been without criticism. As a result, investors and practitioners alike have sought new methods to manage risk for future returns. The CCAPM is one such theory used to adjust the risk premium. The CCAPM is different from the standard CAPM due to the method to calculate beta. Beta in the CCAPM is estimated as the covariance of the ability of investors to use goods or services from investments compared to the market return index which usually the S&P 500 (Bach & Christensen, 2016). The CCAPM is noted below:

$r = rf + \beta c\ (rm - rf)$

The CCAPM equation is similar to the CAPM but factors an investor's wealth consumption or how much an investor will spend.

Risky assets affect the level of spending as noted by the consumption beta. In the equation above, *r* represents the expected return of a stock and *rf* is the risk-free rate. The risk movement of consumption growth measures the consumption beta (βc) and *rm* are the market returns. The CCAPM estimates the movement of the stock market based on consumption growth. Disaster asset pricing, conditional CAPM, and the consumption CAPM are all complex asset pricing models used to price assets, but if investors do not price securities as assumed by the CAPM, then it is no wonder that beta does not explain risk in cross-sectional returns (Berkman, 2013).

Time: Short and long-term holdings. Bach and Christensen (2016) evaluated the CCPAM against the standard CAPM and found that the consumption-based asset-pricing model was better at capturing market value in the cross-section of returns than the CAPM. The cross-sectional significance is only relative to short holding periods of one year and the CCAPM performed as well as the standard CAPM for longer holding periods of five years (Bach & Christensen, 2016).

Benson and Faff (2013) offered a different approach on the simplistic nature of the CAPM, with regards to beta and expected return. They found that using monthly returns instead of annual returns allowed size variability to manifest as a risk indicator in cross-sectional returns (Benson & Faff, 2013). The assumption that CAPM is a short-term indicator of risk is a fallacy that delegitimizes the power of beta. Beta should be retained as an indicator of risk, because those interested in a longer holding period often see the CAPM hold up better than short-term horizons (Benson & Faff, 2013).

The buy and hold pricing strategy are one method researchers have used to justify varying levels of beta risk when establishing an acceptable time horizon (Cohen, Polk, & Vuolteenaho, 2009). Most of the earlier research used trading profits when measuring timing strategies associated with efficient market theory or capital asset pricing models. While holding strategies have produced positive returns, Feldman, Jung, and Klein (2015) uncovered varying results depending on the buy and hold strategy used by investors.

An investment combination using a price level strategy and a long hold horizon strategy resulted in investors becoming price sensitive, meaning the price of a stock was all the investor valued as opposed to expected returns (Cohen et al., 2009). Price became the overwhelming factor in perceived risk (Cohen et al., 2009). The difference in the price level strategy compared to the buy and hold strategy was the belief that investors put a higher premium on the price level as opposed to the return over a specific holding period. Using a buy and hold strategy or timing strategy as a benchmark, compared to traditional asset pricing models, means investors place a higher premium on price levels as a basis for risk diversification, not beta risk. This is significant for financial decision makers that utilize the CAPM, because holding patterns could be as effective at accounting for risk (Cohen et al., 2009).

Lyle and Wang (2015) provided a model that tracked the holding periods of investors using fundamentals that imply expected returns. While the holding periods are time varying, the model was effective at predicting future returns using a forecast for short holding periods (Lyle

& Wang, 2015). The results offered an effective model for investors to capture expected returns for shorter hold periods (Cohen et al., 2009).

Typical investors, with long holding patterns for investment portfolios, need relevant beta measurements for cash flow adjustments, as they are the dominant factor in returns over a prolonged period of time or holding (Cohen et al., 2009). The conclusion, however, was that the longer holding periods of low beta stocks outperformed high beta stocks over a 15-year period compared to growth stocks with high betas that decreased in valuation over the same 15-year period (Cohen et al., 2009). While short-term expected returns are not fully explained by the CAPM, long-term returns are consistent. Cohen et al. (2009) suggested investors that use the CAPM should incorporate a cash flow beta that, over time, provides a true representation of value rather than actual betas for stock returns. Using cash flow betas is more difficult to calculate and requires financial data sometimes not as easily accessed.

Researchers have shown that betas do vary throughout a holding period (Huynh, 2017). Cai, Ren, and Yang (2015) proposed a contemporary time-varying beta to account for the conditional CAPM, which uses adjusted betas over a given time. The time-varying beta assumption was based on the premise that betas fluctuate over time depending on an organization's cash flow (Cai et al., 2015). However, estimating the time-varying betas requires precise estimations, and to truly capture beta as a function of time requires beta estimations to have specific variables (Cai et al., 2015). The specific variables used by investors for time-varying betas are those developed by Ferson and Harvey (1999) to measure the difference in beta variables. Variables for time-varying beta include Treasury Bills, corporate bond yields, and Treasury bond yields. Ferson and Harvey (1999) conceded that the asset allocation puzzle illustrated how advisors do not question core principles of asset allocation; rather, they take the portfolio allocation and try to explain away or ignore data inconsistencies. Investors and advisors have been observed to ignore data so that the data fits their desired asset allocation narrative (Cai et al., 2015).

Using a longer investment horizon is more reasonable considering most investors do not use a single month to invest (Blitz et al., 2014). Complete information and rationality are paramount in the CAPM assumption process, but they create a problem because most investors do not use the information in rational decision-making processes (Blitz et al., 2014). Overconfidence, attention grabbing stocks, and other behavioral accounting measures prevented investment professionals from making rational decisions (Blitz et al., 2014). Evaluating behavioral tendencies between investors has resulted in researchers looking at how accounting information and an organization's financial data became more relevant than in the past, as a way to establish risk. One assumption regarding the behavior of investment professionals is that their behavior is rational and risk-adverse (Blitz et al., 2014).

Dawson (2015) argued the original assumptions of the CAPM are not without needed additional support. The relationship between systematic risk and risk aversion remains a dominant force and the intent of technical market analysis is still needed to contrast a well-diversified portfolio, even if investors are not able to beat the market (Dawson, 2015). The CAPM has led to longer holding periods, but it has also fostered an environment where investors seek higher and higher returns on average (Dawson, 2015).

Cost of capital and growth. Schlueter and Sievers (2014) expanded on the impact of accounting information when calculating market betas. The appropriate accounting measures can affect beta calculations (Schlueter & Sievers, 2014). The CAPM, even with the concerns around beta, still holds key information for estimating systematic risk (Schlueter & Sievers, 2014). Business risk, which is the main component of market beta, can be difficult to calculate because of the behavioral impact organizational accounting decisions play on available market information (Schlueter & Sievers, 2014).

Kim, Kraft, and Ryan (2013) used financial statements to determine if business risk could play a role in market participation and a firm's cost of capital. A reduction in uncertainty lowers a firm's cost of capital because of the amount of information available (Kim et al., 2013). While investors can calculate an organization's risk using all available market information to compute the CAPM beta, those betas are less than perfect and Kim et al., argued that using financial data to determine cost of capital was more suitable for shareholders.

According to Penman (2010), growth risk is the best metric to capture true business risk. Growth risk is important because it identifies uncertainty of an organization's investment strategy (Schlueter & Sievers, 2014, Penman, 2010). Operational and financial risk are important indicators of risk, but growth risk, specifically net operating assets, will change with the increase or decrease in sales which affects an organizations growth (Penman, 2010). Growth risk is controlled by the level at which an organization's sales will grow or change due to market conditions (Schlueter & Sievers, 2014). The opportunity to use growth risk as a measure of systematic risk is tempered by the availability of accounting information to investors (Schlueter & Sievers, 2014). Earlier research models utilized a beta decomposition approach, which provided a more robust explanation for determining risk factors by using operational and financial data (Schlueter & Sievers, 2014).

Summary of Literature Review. This literature review provided a discussion of the seminal and contemporary theoretical thinking and models pertinent to academic and practitioner efforts to understand the main concepts of the relationship between the CAPM's beta and common stock returns. Modern Portfolio Theory, the Efficient Market Hypothesis, as well as the Two and Three-Factor Models were evaluated for their contributions to and limitations for the present study. Given the limitations highlighted in the varying CAPM models, this review assessed the debate surrounding the methodology and statistical analyses utilized to investigate the relationship between beta, a risk indicator, and actual risk. This literature review also reviewed alternative theories for beta, which provided a greater understanding of the variability in market risk and the foundation for conducting this research.

Transition and Summary of Section 1

The beta anomaly is the general problem to be addressed with this study. To address the research question, this study utilized a quantitative correlation analysis. The research method and design are presented in the following section, as well as, the study design, methodology, data collection and analysis, population, and sample size are discussed.

Section 2: The Project

Section 2 outlines the research method utilized to examine the difference between the expected returns associated with beta and actual stock returns from the Standard and Poor's (S&P) 100 index. This section opens with the purpose statement or the focus of the study followed by a discussion of the role of the researcher and how the researcher will adopt a methodological approach to exam the research data. This section also presents a summary of the significance and justification for conducting this research followed by an outline of the sampling frame including definition of the population, sampling method, and sample size. Section 2 concludes with a discussion on the inferential statistic utilized in the data analysis, in addition to the reliability and validity measures of this quantitative research.

Purpose Statement

The purpose of this quantitative correlational study is to examine the relationship between beta and risk using the CAPM and equities from the S&P 100. According to the CAPM, high-beta stocks produce a higher rate of return compared to low-beta stocks in a perfect market (Hong & Sraer, 2016). Beta is a measure of systematic risk that is difficult to diversify and is represented by the slope of a linear regression analysis plotting market returns (Kadan, Liu, & Liu, 2016). Based on the variability from previous research regarding the statistical significance between market returns and benchmark indexes, the relationship between beta and systematic risk needs further examination. The varying statistical relationship has been the foundation to establish a portfolio's risk premium and the expected return for investors (Cederburg & O'Doherty, 2016). There is no conclusive evidence cited in the literature that beta is an accurate reflection of systematic risk. When calculating beta, Kadan et al. (2016) highlighted discrepancies found when risk estimations used portfolios with distribution anomalies, such as market disasters. Hong and Sraer (2016) highlighted the discrepancy between beta and market returns and focused on the over price of high-beta assets compared to overall market returns. Kadan et al. argued beta only used the variance of risk to define systematic risk and did not reflect other market conditions.

Role of the Researcher

The researcher's role for this study was to collect archival stock data to conduct statistical analysis between research variables. The researcher adopted a quantitative correlational design to examine a possible systematic relationship between the expected returns associated with beta and the actual returns for stocks listed in the S&P 100 index. Quantitative research methods are appropriate when using large data sets with statistical analysis (Creswell, 2013). The researcher used S&P 100 archival stock data from Yahoo Finance, from January 1, 2010 through December 1, 2018 (108 months), to determine if a relationship between the independent variable (expected returns associated with beta) and the dependent variable (actual stock returns) exists. The researcher sorted data by year to create the portfolio formation period, the estimation period, and test period (Theriou, Aggelidis, Maditinos, & Sevic, 2010). The researcher used a correlational design and did not directly manipulate the data. Based on the research variables and the type of scale data used for this research project, the researcher used the Pearson correlation coefficient as the parametric statistic. The Pearson correlation coefficient is suitable for two variables that have a linear relationship (Morgan, Leech, Gloeckner, & Barrett, 2011). The researcher measured the extent to which the independent variable (IV) contributed to, or could predict changes in, the dependent variable (DV). The researcher used statistical analysis to determine whether to reject the null hypothesis, and if a statistically significant relationship existed.

Participants

The researcher used the S&P 100 constituents as the basis for the archival data used to examine if a relationship exists between beta and stock returns for stocks traded in the New York Stock Exchange (NYSE). Accordingly, the researcher did not use human participants for this study. The researcher collected data accessed via Yahoo Finance, which is publicly available, to create portfolios of companies based on calculated beta values from January 1, 2010 through December 1, 2018. Cenesizoglu et al. (2016) argued that the 36 months and 60 months of monthly returns were better estimation periods to use for research, compared to 24 months estimation. The researcher chose to use 108 months of existing data segregated into 36-month periods for portfolio formation, estimation period, and test period (Bollen, 2010; Chaudhary, 2016; Theriou et al., 2010). Using companies listed in the NYSE, the researcher isolated companies from the S&P 100 index for use as the sample data, because this data set included stocks from large, blue chip companies across multiple industries within the NYSE (Bollen, 2010). Researchers believe the stocks listed in the S&P 100 have a constant index weight, meaning stochastic weights have an insignificant impact to empirical testing (Driessen, Maenhout, & Vilkov, 2009).

Research Method and Design

The research methodology is the framework used to guide research, while the research design provides the steps taken to collect and analyze data for answering the research question (Creswell, 2013). The following section outlines the rationale for the research method and design for this study. The research method and design address the research problem and justify the purpose for completing this study.

Discussion of Method. The researcher adopted a quantitative research methodology with a correlational design to examine whether a relationship exists between the expected returns associated with beta and actual stock returns. Characteristics of quantitative research often include numerical data and statistical analysis (Watson, 2014). Researchers use quantitative research methods to quantify a problem, using numerical data, to evaluate theories by measuring a relationship between variables (Creswell, 2013).

The researcher chose this method over qualitative and mixed methodologies because of the type of data and variables used to address the research problem. The researcher used archival numerical data to conduct statistical analysis to determine whether a relationship exists between the expected returns associated with beta and actual stock returns. Quantitative research provides a mechanism to capture analytical generalizations from the sample to the target population (O’Rourke, Duggleby, & Fraser, 2015). Earlier researchers used quantitative research methodology to measure the relationship between risk and market returns, which were appropriate for this study (Banz, 1980; Fama & French, 1992, 1996, 2004; Fama & MacBeth, 1973; Roll, 1977). The researcher adopted a quantitative approach because quantitative studies are suited for large data sets and do not require in-depth contextual information (Creswell, 2013).

Discussion of design. The researcher chose a correlational design for this study. A correlational research design enables the researcher to collect data to verify whether a relationship exists between two or more variables (Simon & Goes, 2013). The objective in using a correlational research design is to measure two or more variables and determine if a statistically significant relationship exists (Creswell, 2013). The researcher analyzed the archival stock data for statistical significance with this type of research design.

The correlational design of previous researchers (Banz, 1980; Fama & French, 1992, 1996, 2004; Fama & MacBeth, 1973; Roll, 1977) provided the justification for using a correlational research design and archival data to answer the research questions. A systematic relationship between beta and actual returns are shown to exist when tested against stock data for the Dow Jones Industrial Average (DJIA), National Association of Securities Dealers (NASDAQ), American Stock Exchange (AMEX), NYSE, Indian Stock Market (NSE), Australian Stock Market (ASX), and the Turkish Stock Market (BIST) (Bollen, 2010; Chaudhary, 2016, Terregrossa & Eraslan, 2016). The gap in literature centered around the testing of the S&P 100 index constituents to determine if a systematic relationship between beta and actual returns existed or if there was a difference in returns based on beta category.

The researcher used archival monthly returns for each stock listed in the S&P 100 as of January 1, 2010 as the sample period. The data are divided into 36-month periods to create a portfolio formation period, an estimation period, and a test period. In the portfolio formation period, the researcher used the first 36 months of data (monthly returns) to calculate beta for each stock. Beta estimates were calculated by regressing the stock's return against the proxy market returns, in this case the S&P 500. The researcher used the S&P 500 as the market proxy to benchmark against individual stocks because it is a broad proxy of the 500 largest companies and covers all industries. The beta coefficient for each stock is estimated to create portfolios based on high, strong, and low beta (Terregrossa & Eraslan, 2016).

In the estimation period, the researcher used the next 36 months of monthly returns for each portfolio's stock and averaged the returns to calculate the portfolio's monthly returns. Stocks were sorted based on the beta estimation from highest to lowest, to form portfolios (Bollen, 2010; Chaudhary, 2016, Terregrossa & Erasian, 2016). The high beta stocks (1.01 and higher) comprised Portfolio 1, Portfolio 2 contained strong beta stocks (1.00), and Portfolio 3 contained low beta stocks (0.99 and below). The researcher constructed three portfolios based on the three categories for beta. The portfolio's returns were used to estimate the portfolio beta using the same method as the portfolio formation beta estimate (Bollen, 2010; Chaudhary, 2016, Terregrossa & Erasian, 2016).

In the test period, the researcher used the final 36 months of arcival data and averaged the monthly returns and conducted statistica analysis against the portfolio's beta. The researcher used the data to determine if there is statistical significance between the portfolio's beta and actual returns (Terregrossa & Erasian, 2016). A positive correlation exists when portfolio betas and actual returns have a positively (negatively) relationship and if they are above (below) market returns (Bollen, 2010).

Bollen (2010) determined any stock traded in a specified market would be a sufficient dataset to test the hypothesis that a relationship exists between the expected returns associated with beta and actual stock returns. Bilinski and Lyssimachou (2014) evaluated this hypothesis when analyzing the relationship between the CAPM and stock returns and concluded that market beta was an indicator of risk. Baker et al. (2011) also used this approach to research the low beta anomaly and stock returns. The researcher chose correlational research design over other quantitative research designs due to the nature of the research questions and the categories of measurement of the independent and dependent variables. The researcher deemed this design more appropriate based on measuring the relationship between two variables without manipulation, which is the core of correlational design. The other rejected quantitative designs, including descriptive, quasi-experimental, and experimental, would have required the researcher to directly manipulate or observe data.

Summary of research method and design. The quantitative research method was the most appropriate method because the researcher used numerical data to determine if a statistical relationship existed between stock returns and beta. The researcher used a correlational design to measure if a relationship existed between the research variables, beta, and expected returns.

Population and Sampling

The researcher designed this quantitative correlational project to answer the research questions, if there is a relationship between the expected returns associated with beta and the actual stock returns or is there a difference between beta category and actual stock returns. The researcher selected all the stocks in the S&P 100 as the population for the study and focused on the companies listed at the beginning of the sample period. A discussion of the population and sample method follows to explain the rationale for the selection.

Discussion of Population. The researcher chose the companies that comprise the S&P 100 index as the population for this study based on prior researchers focusing on US stock market returns and a gap in the literature that did not focus on index stocks (Banz, 1981; Cenesizoglu et al., 2016; Fama & French, 1992; Fama & Macbeth, 1973; Sita, 2016). The S&P 100 index represents the largest and most established companies from the S&P 500. The S&P 100 consists of 100 companies at any given time with stocks being added or removed based on the S&P index criteria inclusion into the index.

Discussion of Sampling. The researcher used the majority of the population for the sample size. Due to stocks being added or removed from the S&P 100 index, only stocks listed at the beginning of the study period were used to avoid incomplete data. As of January 1, 2010, 100 companies were listed in the S&P 100 index. Companies included in the sample that are delisted during the full 108 months of data will be removed from the sample size to avoid delisting bias. Delisting is when a stock is no longer traded on a stock market due to bankruptcy or performance related issues (Campbell et al., 2018). Delisting bias occurs when the delisted returns are not available to accurately calculate returns for a portfolio beta (Shumway, 1997). Those companies that comprised the S&P 100, on January 1, 2010 and did not delist, were used throughout the study for consistency. The S&P 100 historically moves a company on or off the index if the company has a market capitalization that falls below the established S&P threshold or if the company engages in a merger or acquisition. Other criteria used by the S&P 100 to add or remove companies also include whether the company is a United States (U.S.) based organization that is listed in the S&P 500 index and whether the organization follows United States accounting standards.

The researcher used companies from the S&P 100 index because of the large market capitalization from well established companies, to avoid delisting bias observed with larger stock data (i.e. all stocks traded in the NYSE), and to answer the research questions (Campbell, Turner,

& Ye, 2018). Compared to the stocks in the S&P 500 index, the S&P 100 companies are more established with longer listing periods, which helps to avoid delisting bias (S&P 100 Indices, 2018). The S&P 100 has shown to have higher implied risk compared to actual risk (Buraschi, Trojani, & Vedolin, 2014; Stivers & Sun, 2013). A list of S&P 100 companies as of January 1, 2010 can be found in Appendix A.

Summary of population and sampling. Companies listed in the S&P 100 have large market caps, are considered blue chip stocks, are more stable than companies outside the top 100, and provide high quality, widely used products and services (S&P 100 Indices, 2018). The characteristics of the sample used for this study were homogenous in that all the companies listed in the S&P 100 are large and financially important for a risk/return analysis (Stivers & Sun, 2013).

Data Collection

The following section provides an outline of the data collection methods used and how the variables are important in determining whether a relationship exists between actual market returns and beta. The researcher compared actual market returns to expected returns, based on beta calculations. This is followed by a description of the data collection technique and how the researcher organized the data. This section defines the archival data variables used to answer the research question and how those variables were collected and organized.

Instruments. The data research tabulations and analyses were conducted using Microsoft Excel and the Statistical Package for the Social Sciences (SPSS). SPSS is a research software tool used for complex statistical analysis. SPSS was the primary statistical package used to understand the relationship between variables. The researcher did not use any other interview or survey material for this project.

Data collection techniques. The data used in this project were obtained from publicly available sources. The primary source was Yahoo! Finance. The researcher also used the Google Finance and Morningstar websites to verify Yahoo! Finance data accuracy. S&P 100 historical constituents for January 1, 2010 were populated using Siblis Research Ltd and downloaded into Excel. The researcher accessed Yahoo! Finance.com and entered each individual company used for the sample and download each month of stock data. Yahoo! Finance.com allows users to customize the data under the historical tab. The historical date range was entered and the data frequency of monthly was selected, which populated the closing day stock price for each month. The archival data was downloaded into Microsoft Excel and includes the date (first day of each month), the open price, the day's high and low price, closing price, adjusted close, and trading volume. The researcher organized data into an Excel worksheet alphabetically. The raw data is available by request from the researcher.

Once all archival stock data was downloaded into Excel, the researcher calculated beta for each company. Unnecessary data, such as trade volume and high/low value each month, was deleted to only include the date and adjusted close price. Next the researcher downloaded the archival adjusted close data for S&P 500, to serve as the market proxy, using the same date range. The researcher pasted the market proxy data into the company stock data in the adjacent column to the right of the adjusted close price. The monthly returns and the market proxy returns were calculated in Excel by taking the newest monthly close price and dividing into the next monthly price minus 1. For example, December 2018 stock price was divided into the November 2018 stock price minus 1. This was repeated to the final monthly stock price. The researcher used a linear regression (slope function in Excel) to calculate the beta for each stock against the market proxy, in this case the S&P 500. The researcher sorted data alphabetically based on the company name using Microsoft Excel.

Data organization techniques. The researcher organized each company alphabetically by company name, stock symbol, date, adjusted close, and beta. The adjusted closing price accounted for splits and dividends, per Yahoo! Finance.com. Previous researchers used three to five years to estimate beta with daily or monthly returns for each stock and regressed beta against actual returns, which is the standard for beta estimates and testing (Cenesizoglu et al., 2016; Terregrossa & Eraslan, 2016). Cenesizoglu et al. (2016) determined 36 months and 60 months beta estimates were more accurate than 24 months. Multiple researchers used 36 months of data for beta estimates while others used 60 months of data to estimate beta (Bollen, 2010; Chaudhary, 2016, Terregrossa & Erasian, 2016; Theriou et al., 2010). For this effort, the researcher used 36 months of archival returns for portfolio creation. All data and analysis were stored on a computer and flash drive owned by the researcher. The flash drive served as the primary storage device and the computer provided a backup for all files and data in case of file corruption or damage to the flash drive. The researcher systematically updated files each day as data and notes were collected.

The sample period was organized into portfolios for the formation period, estimation period, and the test period. The first 36 months of data were used for the portfolio formation period in which beta estimates were calculated using actual returns and regressed against the market proxy, in this case the S&P 500 (Bollen, 2010; Chaudhary, 2016). The betas for each stock were sorted based on highest beta to lowest beta to create portfolios. For the estimation period, the average monthly returns for each of the portfolio's constituents were calculated using the next 36 months of data to produce the monthly portfolio returns (Chaudhary, 2016). The researcher created portfolio betas by regressing the monthly returns against actual returns of the market proxy. The portfolio betas were regressed against the monthly portfolio returns over the final 36-month test period (Chaudhary, 2016).

Summary of data collection. The researcher conducted this quantitative study to determine if a relationship existed between the expected returns associated with beta and actual stock returns for companies listed in the S&P 100. The researcher used archival data from Yahoo! Finance to calculate beta estimations and to conduct regression analyses. Human participants were not used to answer research questions. The archival data served as the foundation to conduct statistical analysis to answer the research question.

Data Analysis

The data analysis section provides a summary of the variables of interest to the study, including a discussion of the data types or categories of measurements for the variables, and why they were appropriate for this study. This is followed by an outline of the process used to determine the reliability and validity of the data. Finally, this section concludes with a summary of Section Two and an introduction to the field study.

Variables used in the study. The researcher employed an independent variable (expected returns associated with beta), dependent variable (actual stock returns), and two mitigating variables (beta category & industry sector) for this quantitative correlational research project. Beta estimates are categorized as low or high based on the beta value. A beta value of less than 1.00 is categorized as a low beta and a beta with a value greater than 1.00 is categorized as a high beta. Beta values equal to 1.00 are strong beta values that strongly correlate with the market proxy but would not increase the likelihood of excess returns. A correlational design compares two or more variables using statistical models to answer a research question (Creswell, 2013). The researcher selected a paired sample t-test, based on the two variable difference research questions (Morgan et al., 2011).

The beta-return relationship is the foundation for the CAPM and fundamental in modern financial research (Sita, 2018). Previous work from Stivers and Sun (2016), Cenesizoglu et al. (2016), and Sita (2018) utilized beta and market returns for the independent and dependent variables. Both the independent and dependent variables are scale data types, while the mitigating variables are both ordinal and nominal for beta categories and industry sector, respectively. The researcher used these variables to conduct statistical analysis in order to either reject or accept the null hypothesis. This technique is best suited to study the difference between the risk/return relationship based on the research question and variables used (Morgan et al., 2011).

Table 1

Correlational Model Variable Table

Correlational Model Variable			
Variable	Description	Variable Type	Data Type
Beta	Measure of a stock's volatility relative to the market	Independent Variable	Scale
Actual Returns	Gains/loss from a stock during a period of time	Dependent Variable	Scale
Beta Categories	Low, strong, & high	Mitigating Variable	Ordinal
Range			
Low Beta	*0.99 and below*		
Strong Beta	*1*		
High Beta	*1.01 and above*		
Industry Sector	11 Global Industry Classification Standards	Mitigating Variable	Nominal
Range			
Energy	*Energy equipment, services, oil & gas*		
Materials	*Chemical, construction, metal, mining & paper*		
Industry	*Capital goods, commercial, transportation*		
Consumer Discretionary	*Auto, durables, hospitality & retail*		
Consumer Staples	*Food, beverage & household*		
Health Care	*Health care equipment, pharmaceuticals & biotechnology*		
Financials	*Banks, diversified financials & insurance*		
Information Technology	*Software, hardware & semiconductors*		
Telecommunication Services	*Telecommunication services, wireless, media, entertainment & interactive*		
Utilities	*Electric, gas, water & renewables*		
Real Estate	*Equity real estate, real estate management & development*		

Statistical Test. The researcher addressed the problem statement as to whether beta (IV) was an accurate indicator of risk for S&P 100 constituent actual returns (DV) based on beta categories (MV) and industry sector (MV). The data were analyzed using Microsoft Excel and SSPS. The study period consisted of data from January 1, 2010 through December 1, 2018. The researcher calculated the IV variable, beta, for the S&P 100 and the S&P 500 by using the dependent variable, archival monthly returns and sorted into a formation period, estimation period, and the test period. The monthly returns from the first 36 months of data, for each stock in the S&P 100 and the market proxy, were used to calculate the percent change from month to month. In excel, the researcher used the slope function to regress the percent change for the S&P 100 company stock against the S&P 500 benchmark. This process was duplicated for each stock listed in the S&P 100 index. Each constituent beta was sorted from low to high beta to construct portfolios based on beta category. Low beta stocks include constituents with a beta of .99 and lower. Strong beta stocks include constituents with a beta of 1.0 and high beta stocks include constituents with a beta of 1.0 and higher. Using the next 36 months of archival data, the stock betas are created and averaged to create a portfolio beta. The final 36 months of archival data is used to calculate excess portfolio returns by averaging the excess returns for each stock in the portfolio and regressing against the portfolio beta.

Descriptive statistics were used in order to complete statistical evaluations as to whether the results meet the assumptions of the hypotheses. The researcher used a One-way Analysis of Variance (ANOVA) because H1 is testing three or more levels and according to Morgan et al. (2011), the One-Way ANOVA is the appropriate statistic to use for scale data with one independent variable with three or more groups, differentiated between low, strong, & high beta, and one dependent variable. For the null hypothesis and subsequent null sub-hypotheses, the researcher used an Independent Samples t-Test because the independent variable has one factor with two groups and one dependent variable (Morgan et al., 2011). For hypothesis H2 and the null hypothesis H_o2 the researcher again used the One-way ANOVA because of one independent variable with three or more levels and a dependent variable with scale data.

Hypothesis 1. The hypotheses are connected to research questions one as follows:

RQ1: Is beta an accurate indicator of risk or excess returns for individual stocks listed in the S&P 100 index when compared to the S&P 500 index as a benchmark?

H1: There is a statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the three beta category.

H_o1: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the three beta category.

H_o1a: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the low beta category.

H_o1b: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the strong beta category.

H_o1c: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the high beta category.

Hypothesis 2. H2: There is a statistically significant difference in average monthly returns within the three beta categories (low, strong, & high).

H_o2: There is no statistically significant difference in average monthly returns within the three beta categories (low, strong, & high).

Hypothesis 3. For association questions and/or hypotheses, Morgan et al. (2011) suggested the appropriate inferential statistic is the Pearson correlation coefficient *r* or the Pearson (*r*) when research variables are scale within related subjects. Using the beta category data from the portfolio creation, the researcher used the Pearson (*r*) bivariate parametric statistic to determine if an associate existed between beta category and average monthly stock returns. Descriptive statistics were used to evaluate if the variables would meet the assumptions of the RQ and hypotheses.

RQ2: Are any of the three beta categories (low, strong, & high) a more accurate indicator of risk or excess returns for individual stocks listed in the S&P 100 index when compared to the S&P 500 index as a benchmark?

The hypotheses for the research question are as follows:

H3: There is a statistically significant association between average monthly returns for stocks in the S&P 100 and beta.

H_o3: There is no statistically significant association between average monthly returns for stocks in the S&P 100 and beta.

H_o3a: There is no statistically significant association between average monthly returns for stocks in the S&P 100 low beta category and the beta for the low beta category.

H_o3b: There is no statistically significant association between average monthly returns for stocks in the S&P 100 strong beta category and the beta for the strong beta category.

H_o3c: There is no statistically significant association between average monthly returns for stocks in the S&P 100 high beta category and the beta for the high beta category.

To understand the difference between the independent variable, dependent variable, and the mitigating variable, industry sector, the researcher tested the correlation between variables.

Hypothesis 4. The researcher sorted archival stock data into 11 portfolios based on the Global Industry Classification Standard (GICS). The same process of calculating stock betas for research questions one and two was followed for the industry classification portfolios to create company betas. Using the next 36 months of archival data, the company betas were created and averaged to create the industry category beta. The final 36 months of archival data was used to calculate excess industry returns by averaging the excess returns for each stock in the industry portfolio and regressing against the portfolio beta. Descriptive statistics were used to ensure the variables met the hypotheses assumptions. Due to H4 and H_o4 asking a difference question, having one independent variable with three or more categories, and a one dependent variable with scale data, the One-way ANOVA test was used as recommended by Morgan et al. (2011. For the sub-hypothesis, the researcher used the One-way ANOVA because the one independent variable has three or more groups (low, strong, & high) and one dependent variable.

RQ3: Is beta a better indicator of risk or excess returns for the eleven industry sector stocks listed in the S&P 100 index compared to the S&P 500 index as a benchmark?

The hypotheses for the research question are as follows:

H4: There is a statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the 11 Global Industry Classification Standard (GICS) stocks in the S&P 100.

H_o4: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the 11 Global Industry Classification Standard (GICS) stocks in the S&P 100.

H_o4a: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the energy sector stocks in the S&P 100.

H_o4_a: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the materials sector stocks in the S&P 100.

H_o4_b: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the industrials sector stocks in the S&P 100.

H_o4_c: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the consumer discretionary sector stocks in the S&P 100.

H_o4_d: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the consumer staples sector stocks in the S&P 100.

H_o4_e: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the health care sector stocks in the S&P 100.

H_o4_f: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the financial sector stocks in the S&P 100.

H_o4_g: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the information technology sector stocks in the S&P 100.

H_o4_h: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the telecommunications services sector stocks in the S&P 100.

H_o4_i: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the utilities sector stocks in the S&P 100.

H_o4_j: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the real estate sector stocks in the S&P 100.

Summary of Data Analysis. The data analysis section provides a summary of the variables used to answer the research question and how those variables relate to the research question. The researcher used beta as the independent variable, actual stock returns as the dependent variable, and beta categories/industry sector as mitigating variables. The research question and hypotheses guided the researcher to the appropriate statistic based on whether the questions regarded a difference or a relationship. A One-way ANOVA was used to determine if there was a difference between one independent variable beta, with three or more levels (low, strong, & high) and scale dependent variable (actual returns). An Independent Samples *t*-Test was used for the one independent variable with two categories. The Pearson (*r*) was utilized to determine if there was an association between two variables within the same subjects.

Reliability and Validity

Researchers have reliability and validity issues, regardless of whether the researcher uses quantitative, qualitative, or mixed methods (Creswell, 2013). The instruments a researcher utilizes to collect data can also create issues with reliability and validity. Researchers must take care to minimize threats to their research projects. The threats to reliability and validity for this doctoral research project are further explored in this section.

Reliability. Heale and Twycross (2015) defined reliability as the consistency of a method to measure data while Salkind (2013) expanded on the definition of reliability to include the quality and consistency of data so that the results are repeatable and confirmed by other researchers. To achieve reliability, researchers must use an instrument or other data gathering technique(s) to ensure data accuracy (Creswell, 2013). The researcher used the quantitative research method, so the reliability for this quantitative study focused on the accuracy of the data collection so that other researchers could repeat or confirm the results. The researcher did not use an instrument to gather data, but instead used archival data from publicly available sources. To provide reliable data, the researcher used data from Yahoo! Finance website as the primary source of data and randomly checked data from the Google Finance and Morningstar websites to ensure that the daily returns were consistent.

The growth in researchers storing data for future exploration has increased the use of archival data and has made accessibility easier (Turiano, 2014). The growth in international research and the advances of technology have led to greater accessibly to research data (Turiano, 2014). Archival data used in mirco-organizational research, such as this study, can increase statistical power by examining data over a specific time (Barnes, Dang, Leavitt, Guarana, & Uhlmann, 2015). The archival data used for this research project consisted of archival data, rather than data gathered from special surveys or instruments.

Validity. Validity is the extent to which a concept is accurately measured during quantitative research (Heale & Twycross, 2015). The three major types of validity are content validity, construct validity, and criterion validity (Creswell, 2013; Heale & Twycross, 2015). Following is a summary of the validity threats related to this study.

Content validity is concerned with whether the instrument used in a research project measures the content or data as expected (Creswell, 2013). The threats to content validity are non-statistical in that content validity determines whether the content data is enough to represent a sample behavior. The researcher did not use an instrument to measure behavior and used archival data to minimize the threat of content validity.

Criterion validity refers to the degree of correlation between the statistical test and the research variables and whether the results correlate with other test results (Creswell, 2013; Heale & Twycross, 2015). The researcher did not use an existing instrument but archival data. To address the research question, the researcher used a simple linear regression to determine if a correlation existed between the variables. The use of a simple linear regression was consistent with the statistical approach used by prior researchers (Bilinski & Lyssimachou, 2014; Chaudhary, 2016; Fischer, Blanco-Fernandez, & Winker, 2016).

Construct validity refers to the inferences the researcher can draw from test results (Heale & Twycross, 2015). Creswell (2013) implied that in order to achieve objectivity, researchers must focus more on test scores and whether the scores have a positive impact on the study to achieve construct validity. Threats to construct validity include the lack of suitable measures for variables (Creswell, 2013). In this study, the researcher used the appropriate statistical measure, a simple linear regression, as described by prior researchers (Bilinski & Lyssimachou, 2014; Cenesizoglu et al. 2016). As a result, the researcher minimized construct validity threats.

Summary of reliability and validity. The researcher designed this study to address the research questions and to take all reasonable steps to limit reliability or validity threats. Creswell

(2013) indicated that it is impossible to remove all threats to reliability and validity, although researchers can take reasonable measures to minimize threats. The researcher took all logical steps to alleviate identified threats by modeling the study from prior research.

Transition and Summary of Section 2

Section 2 provided an outline of the research method utilized to examine the relationship between the expected returns associated with beta and the actual stock returns in the S&P 100. This section began with a review of the purpose statement and the focus of the study and was followed by a summary of the role of researcher and a discussion concerning participants for the study. Next, was a summary of the research method and design for this correlational quantitative research project which outlined the population and sample and how data was collected and analyzed. Section 2 concluded with a discussion on the inferential statistic utilized in the data analysis, in addition to the reliability and validity measures of this quantitative research.

The following section includes an overview of the study and a presentation of the findings. It provides a detailed discussion of the statistical tests performed and links the results to the research questions. Finally, the researcher applies the results to professional practice, provides recommendations for action, and reflects on the research experience.

Section 3: Application to Professional Practice and Implications for Change

The following section presents the findings of the research project, applications for professional practice, and implications for further research. This section begins with an overview of the study to explain how it pertains to the field of accounting, why the research study was conducted, and the methodology used to conduct the study. The presentation of the findings provides a detailed discussion of the descriptive statistics, statistical tests performed, and a link to each hypothesis and the research questions. Based on the results, the conclusions are presented, along with recommendations for future research. The final section reflects on key learning points, any possible change of thinking, and Biblical principles for this research project.

Overview of the Study

The relationship between market risk and expected returns has been one of the most important research topics to address systematic risk (Bollen, 2010; Chaudhary, 2016, Terregrossa & Erasian, 2016). Researchers have found the beta anomaly to be a financial puzzle which affects how investors diversify risk (Bilinski & Lyssimachou, 2014; Cenesizoglu et al. 2016). This current study expands on prior research, which was inconclusive as to whether the risk indicator beta could predict expected average monthly returns with statistical significance. The researcher compared the difference between monthly average returns of the S&P 100 and the benchmark (S&P 500) against the three beta categories (high, strong, & low). Next, the researcher compared the association between average monthly returns and beta. Finally, the researcher compared the difference between average monthly returns and industry sector compared to the three beta categories. See Table 1 below, which includes the study variables.

Table 2

Correlational Model Variable Table

Correlational Model Variable			
Variable	Description	Variable Type	Data Type
Beta	Measure of a stock's volatility relative to the market	Independent Variable	Scale
Actual Returns	Gains/loss from a stock during a period of time	Dependent Variable	Scale
Beta Categories	Low, strong, & high	Mitigating Variable	Ordinal
Range			
Low Beta	*0.99 and below*		
Strong Beta	*1*		
High Beta	*1.01 and above*		
Industry Sector	11 Global Industry Classification Standards	Mitigating Variable	Nominal
Range			
Energy	*Energy equipment, services, oil & gas*		
Materials	*Chemical, construction, metal, mining & paper*		
Industry	*Capital goods, commercial, transportation*		
Consumer Discretionary	*Auto, durables, hospitality & retail*		
Consumer Staples	*Food, beverage & household*		
Health Care	*Health care equipment, pharmaceuticals & biotechnology*		
Financials	*Banks, diversified financials & insurance*		
Information Technology	*Software, hardware & semiconductors*		
Telecommunication Services	*Telecommunication services, wireless, media, entertainment & interactive*		
Utilities	*Electric, gas, water & renewables*		
Real Estate	*Equity real estate, real estate management & development*		

Presentation of the Findings

The study used a sample of archival data for stocks listed in the S&P 100 between January 1, 2010 through December 31, 2018 to determine if there was a difference in returns based on beta. The research questions were divided into three sections. First, the researcher sought to understand the difference between stock returns for the S&P 100 compared to the benchmark, in this case the S&P 500, and based on the beta category (low, strong, & high). Next, the researcher sought to determine if an association existed between beta and average monthly returns. Finally, the researcher used the industry classification to determine if there was a difference between industry sectors and beta.

The data was organized into beta categories (low, strong, & high) by calculating the beta for each stock listed in the S&P 100. The stocks were also sorted by industry sectors. There were 100 stocks listed in the S&P 100 as of January 1, 2010. Of the 100 stocks, there were eight companies delisted during 2010. These companies were excluded from the data analysis bringing the total stocks to 92. There were 40 stocks that comprised the low beta category, 2 stocks in the strong category, and 50 stocks in the high beta category. See the beta category count in Table 2 below.

Table 3

Count of Stocks per Beta Category

Category	Count
High Beta	50
Strong Beta	2
Low Beta	40

The data were also sorted based on the Global Industry Classification System (GICS) industry classification. The count of the stocks for each category are listed in Table3. MSCI and the S&P indices created the GICS as an investment tool to organize industries. There are 11 industry classifications and the researcher organized the stock data based on industry classification.

Table 3

Count of Stocks per Industry Sector

Industry Sector	Count
Energy	9
Materials	6
Industrial	12
Consumer Discretionary	7
Consumer Staples	9
Health Care	12
Financials	14
Information Technology	12
Telecommunication Services	6
Utilities	4
Real Estate	1

The conclusions for each research question and hypothesis are addressed and related to the overall body of research regarding beta and market returns in the following section. The researcher will highlight any outliers or discrepancies found in the data and what impact those had to the overall study. The results were not statistically significant for RQ1, RQ2, and RQ3, so the researcher failed to reject each null hypothesis. The findings were consistent with previous studies finding no evidence of a significant relationship between beta and returns (Bilinski & Lyssimachou, 2014). The findings were inconsistent with prior studies in that beta showed association with average monthly returns (Bollen, 2010; Chaudhary, 2016; Sita, 2018; Terregrossa & Eraslan, 2016).

Hypothesis 1. Research question one compared the difference between excess returns and beta from the S&P 100 and the benchmark, in this case the S& P 500. The research question is as follows:

RQ1: Is beta an accurate indicator of risk or excess returns for individual stocks listed in the S&P 100 index when compared to the S&P 500 index as a benchmark?

The subsequent hypotheses compared the difference between the three beta categories and average monthly returns of the S&P 100.

H1: There is a statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the three beta category.

H_o1: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the three beta category.

The researcher used a One-Way ANOVA to compare the difference between two or more independent groups with the dependent variable (Morgan et al., 2011). Table 4 highlights the descriptive statistics for the One-Way ANOVA statistical test and the means to be compared.

The low, strong, and high beta categories are represented by the number of stocks in each category (N).

Table 4

Descriptive Statistics for Average Monthly Return and Beta Category

Descriptives

2016-2018 Avg. Monthly Return

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum	Between-Component Variance
Low		40	1.2542	4.01519	.63486	-.0299	2.5383	-.51	25.42	
Strong		2	-.2218	.62808	.44412	-5.8650	5.4213	-.67	.22	
High		50	.7498	1.41531	.20015	.3476	1.1520	-.83	7.88	
Total		92	.9480	2.84343	.29645	.3591	1.5369	-.83	25.42	
Model	Fixed Effects			2.85864	.29803	.3558	1.5402			
	Random Effects				.29803[a]	-.3343[a]	2.2303[a]			-.16652

Typically, statisticians and researchers test for the assumption of the homogeneity of variance using Levene's test. When the value of the statistical significance in Levene's test is less than < 0.05, then the assumption is violated. This is counter to most statistics because Levene's actually tests to see whether the means of each group are similar. If they are similar, then it means that there is no homogeneity of variance which is a requirement for this inferential statistic. Table 5 represents the Test of Homogeneity of Variances. The significance of the Levene's test was not statistically significant because the equal variances assumed were greater than > 0.05. Average monthly returns were not significant at 0.38, meaning the assumption of the Levene's test was not violated.

Table 5

Test of Homogeneity of Variance for Average Monthly Returns

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
2016-2018 Avg. Monthly Return	Based on Mean	.977	2	89	.380
	Based on Median	.406	2	89	.667
	Based on Median and with adjusted df	.406	2	49.333	.668
	Based on trimmed mean	.421	2	89	.658

Table 6 is divided into between-groups effects (due to the model or experimental effect) and within-group effects (systematic variation in the data). The sum of squares for the model equals 8.45 and degrees of freedom are equal to 2. The test of whether the group means are the same is represented by the *F*- ratio for the between groups. The value for this ratio is .52

In this output, there is a probability of 0.60 that an *F*- ratio of this size would occur if there was no effect (or would occur by chance). As the critical cut off point of < 0.05 was utilized as a criterion of statistical significance, the output of the analysis fails to reject the null hypothesis that there was no statistically significant effect of beta category on return as the significance of 0.60 which is larger than the critical cut off point of < 0.05. This is consistent with results from previous studies finding no significant evidence of beta and average monthly returns (Bilinski & Lyssimachou, 2014). Fama and French (1992) found similar results in the beta/return anomaly concluding the validity of the CAPM in predicting return was flawed.

$F(2,89) = .52$, $p. > .05$ (= .60)

Table 6

Analysis of Variance for Average Monthly Returns

ANOVA

2016-2018 Avg. Monthly Return

			Sum of Squares	df	Mean Square	F	Sig.
Between Groups	(Combined)		8.452	2	4.226	.517	.598
	Linear Term	Unweighted	5.654	1	5.654	.692	.408
		Weighted	5.522	1	5.522	.676	.413
		Deviation	2.930	1	2.930	.359	.551
Within Groups			727.294	89	8.172		
Total			735.746	91			

For the subsequent RQ1 hypotheses an Independent Samples *t*-Test was administered to compare the means between the low beta category in S&P 100 and the benchmark to determine if the sample is significantly different.

H_o1a: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the low beta category.

H_o1b: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the strong beta category.

H_o1c: There is no statistically significant difference in monthly average returns between the S&P 500 benchmark and S&P 100 stocks comprising the high beta category.

The assumptions for the Independent Samples *t*-Test are the dependent variables in the two populations are equal, the dependent variable is normally distributed, and the data is independent (Morgan et al., 2011). Table 7 outlines the Group Statistics the different beta categories, which are the descriptive statistics for the Independent Samples *t*-Test and compares the means for the average monthly returns of the S&P 100, the benchmark, and beta category.

Table 7

Group Statistics for the S&P 100 Average Monthly Returns and the Benchmark

Group Statistics

	Beta Category (High 3, Strong 2, Low 1)	N	Mean	Std. Deviation	Std. Error Mean
2016-2018 Avg. Monthly Return	Low	40	1.2542	4.01519	.63486
	High	50	.7498	1.41531	.20015
Benchmark Avg Monthly Return	Low	40	15.7392	.00000	.00000
	High	50	15.7392	.00000	.00000

Group Statistics

	Beta Category (High 3, Strong 2, Low 1)	N	Mean	Std. Deviation	Std. Error Mean
2016-2018 Avg. Monthly Return	Strong	2	-.2218	.62808	.44412
	High	50	.7498	1.41531	.20015
Benchmark Avg Monthly Return	Strong	2	15.7392	.00000	.00000
	High	50	15.7392	.00000	.00000

Group Statistics

	Beta Category (High 3, Strong 2, Low 1)	N	Mean	Std. Deviation	Std. Error Mean
2016-2018 Avg. Monthly Return	Strong	2	-.2218	.62808	.44412
	Low	40	1.2542	4.01519	.63486
Benchmark Avg Monthly Return	Strong	2	15.7392	.00000	.00000
	Low	40	15.7392	.00000	.00000

Table 8 reflects the Independent Samples *t*-test for the benchmark and the S&P 100 average returns. The table shows the average returns from the S&P 100 were not statistically significant for beta category as $p = 0.41$. The critical cut off point was < 0.05. The findings are consistent with Fama and French (1992) which found beta alone was not statistically significant in predicting average monthly returns.

Table 8

Independent Samples t-Test for the S&P 100 Average Monthly Returns and the Benchmark

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
2016-2018 Avg. Monthly Return	Equal variances assumed	1.803	.183	.827	88	.410	.50441	.60968	-.70720	1.71602
	Equal variances not assumed			.758	46.771	.452	.50441	.66566	-.83490	1.84372
Benchmark Avg Monthly Return	Equal variances assumed	.	.	8.985	88	.000	.00000	.00000	.00000	.00000
	Equal variances not assumed			9.297	87.349	.000	.00000	.00000	.00000	.00000

Hypothesis 2. For the second hypotheses for RQ1, the researcher looked at the difference between average returns for the three beta categories. Again, the One-Way ANOVA was administered to compare the independent groups with the dependent variable.

H2: There is a statistically significant difference in average monthly returns within the three beta categories (low, strong, & high).

H_o2: There is no statistically significant difference in average monthly returns within the three beta categories (low, strong, & high).

Table 9 is the descriptive statistics for beta category and average monthly return. The beta category means are compared with the S&P 100 average monthly returns. The Test of Homogeneity of Variances provides the Levene's test to check that the variance of the three beta categories (Table 10). Typically, statisticians and researchers test for the assumption of the homogeneity of variance using Levene's test. When the value of the statistical significance in Levene's test is less than < .05, then the assumption is violated. This is counter to most statistics because Levene's actually tests to see whether the means of each group are similar. If they are similar, then it means that there is no homogeneity of variance which is a requirement for this inferential statistic. Average monthly returns are not significant (p = 0.38) and thus the assumption is not violated.

Figure 4 highlights the mean plots for each beta category, showing the average returns for low beta stocks as higher than strong beta and high beta stocks. This is consistent with prior findings from Cederburg and O'Doherty (2016) that low beta stocks outperform high beta stocks.

Table 9

Descriptive Statistics for Beta Category and Average Monthly Returns

Descriptives

2016-2018 Avg. Monthly Return

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum	Between-Component Variance
Low		40	1.2542	4.01519	.63486	-.0299	2.5383	-.51	25.42	
Strong		2	-.2218	.62808	.44412	-5.8650	5.4213	-.67	.22	
High		50	.7498	1.41531	.20015	.3476	1.1520	-.83	7.88	
Total		92	.9480	2.84343	.29645	.3591	1.5369	-.83	25.42	
Model	Fixed Effects			2.85864	.29803	.3558	1.5402			
	Random Effects				.29803[a]	-.3343[a]	2.2303[a]			-.16652

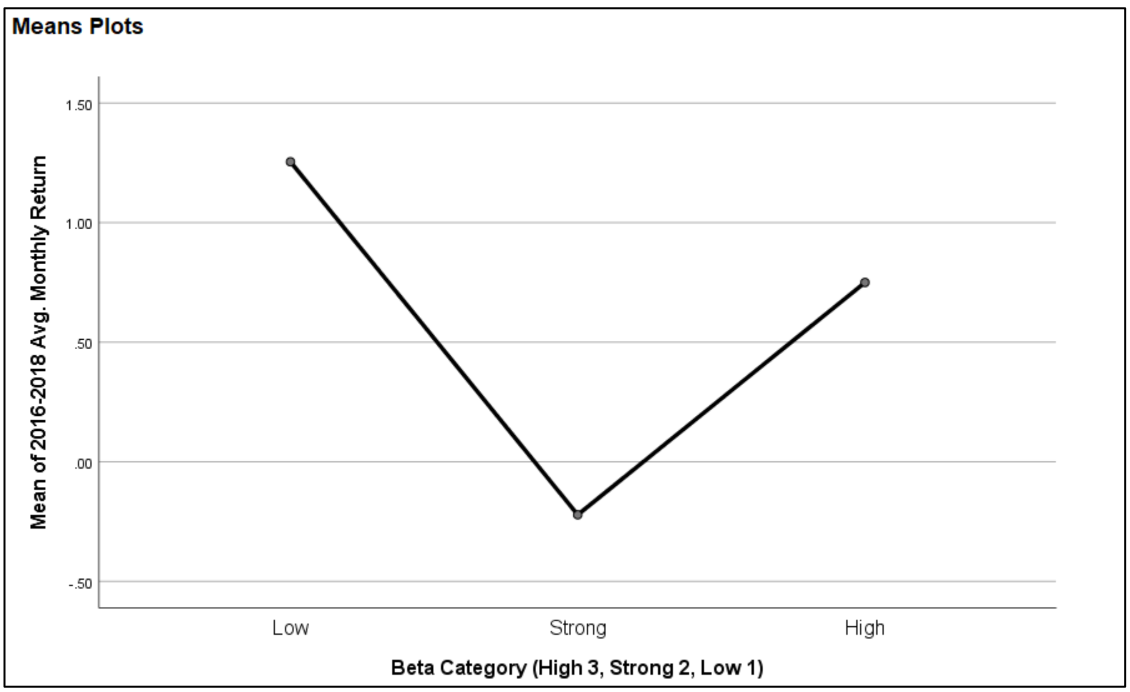


Figure 4. Mean plots for Beta Category and average monthly returns

Table 10

Test of Homogeneity of Variance for Average Monthly Returns and Beta Category

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
2016-2018 Avg. Monthly Return	Based on Mean	.977	2	89	.380
	Based on Median	.406	2	89	.667
	Based on Median and with adjusted df	.406	2	49.333	.668
	Based on trimmed mean	.421	2	89	.658

Table 11 is the ANOVA table and divided into between-groups effects (due to the model or experimental effect) and within-group effects (systematic variation in the data). The sum of squares for the model equals 8.45 and degrees of freedom are equal to 2. The test of whether the group means are the same is represented by the *F*- ratio for the between groups. The value for this ratio is 0.52, which shows there was no statistical significance between average monthly returns and beta category.

In this output, there is a probability of .60 that an *F*- ratio of this size would occur if there was no effect (or would occur by chance). As the critical cut off point of 0.05 was utilized as a criterion of statistical significance, the output of the analysis fails to reject the null hypothesis that there was no statistically significant effect of beta category on return. This is consistent with results from previous studies finding no significant evidence of beta and average monthly returns (Bilinski & Lyssimachou, 2014; Theriou et al., 2010).

$F(2,89) = .52$, $p. > .05$ (= .60)

Table 11

Analysis of Variance for Average Monthly Returns

ANOVA

2016-2018 Avg. Monthly Return

			Sum of Squares	df	Mean Square	F	Sig.
Between Groups	(Combined)		8.452	2	4.226	.517	.598
	Linear Term	Unweighted	5.654	1	5.654	.692	.408
		Weighted	5.522	1	5.522	.676	.413
		Deviation	2.930	1	2.930	.359	.551
Within Groups			727.294	89	8.172		
Total			735.746	91			

Hypothesis 3. RQ2 compared the three beta categories to determine if one category was a better risk indicator for average monthly returns. To determine if there was a statistically significant association between beta and average returns listed in the S&P 100, the researcher used Bivariate Pearson correlation.

RQ2: Are any of the three beta categories (low, strong, & high) a more accurate indicator of risk or excess returns for individual stocks listed in the S&P 100 index when compared to the S&P 500 index as a benchmark?

The hypotheses for the research question are as follows:

H3: There is a statistically significant association between average monthly returns for stocks in the S&P 100 and beta.

H_o3: There is no statistically significant association between average monthly returns for stocks in the S&P 100 and beta.

To investigate whether a statistically significant association between beta and average monthly returns a Pearson Correlation was computed. Table 12 contains the descriptive statistics (mean, standard deviation, and N) for S&P 100 average monthly returns compared to the preceding period beta calculation. The Pearson correlation statistic was calculated, r (90) = -0.003, p = 1.00. The correlation direction was negative, which means the average monthly returns for stocks in the S&P 100 are not correlated to beta (Table 13). A scatterplot analysis for average monthly returns and beta is presented in *Figure 5*. Beta estimations for 2013-2015 and average returns for individual stocks (2016-2018) clustered between a beta 0 and 2 and an s return of 2. The cluster of stocks show a near zero linear line, which is consistent with Fama and French (1992) findings that showed a flat relationship between beta and returns.

Table 12

Descriptive Statistics for Average Monthly Returns and Beta

Descriptive Statistics

	Mean	Std. Deviation	N
2016-2018 Avg. Monthly Return	.9480	2.84343	92
2013-2015 Beta	1.2140	1.57586	92

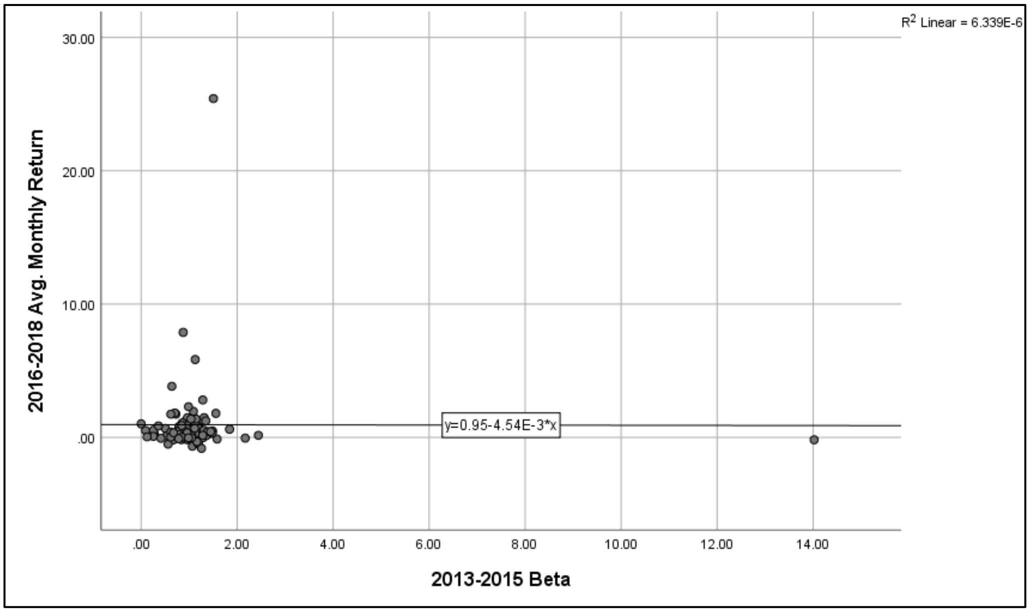
Table 13

Correlation Analysis Statistics for Average Monthly Returns and Beta

Correlations[a]

		2016-2018 Avg. Monthly Return	2013-2015 Beta
2016-2018 Avg. Monthly Return	Pearson Correlation	1	-.003
	Sig. (2-tailed)		.981
2013-2015 Beta	Pearson Correlation	-.003	1
	Sig. (2-tailed)	.981	

a. Listwise N=92



F*igure 5. Scatterplot Analysis for Average Monthly Return and Beta*

As for the subsequent hypotheses, the researcher used the bivariate parametric statistic the Pearson *r* to determine if there was an association between average monthly returns for the S&P 100 stocks and the corresponding beta category (low, strong, & high).

H_o3a: There is no statistically significant association between average monthly returns for stocks in the S&P 100 low beta category and the beta for the low beta category.

H_o3b: There is no statistically significant association between average monthly returns for stocks in the S&P 100 strong beta category and the beta for the strong beta category.

H_o3c: There is no statistically significant association between average monthly returns for stocks in the S&P 100 high beta category and the beta for the high beta category.

To determine if there was a statistically significant association between beta category and average returns listed in the S&P 100, the researcher used Bivariate Pearson correlation. The descriptive statistics for average monthly returns and beta category contain the mean, standard deviation, and N (Table 14).

Table 14

Descriptive Statistics for Average Monthly Retuns and Beta Category

Descriptive Statistics	Mean	Std. Deviation	N
2016-2018 Avg. Monthly Return	.9480	2.84343	92
Beta Category (High 3, Strong 2, Low 1)	2.11	.988	92

The Pearson correlation statistic was calculated, *r* (90) = -0.1, *p* = 0.4 (Table 15). The correlation direction was negative, which means the average monthly returns for stocks in the S&P 100 are not correlated to beta. The scatterplot for beta category and average monthly returns are presented in *Figure 6*, which show a slight high negative for beta and average monthly returns. This means that low beta stocks have a slightly higher return compared to strong or high beta stocks. The findings are consistent with the beta anomaly question in that low beta stocks tend to outperform high beta stocks, but when compared against beta categories there was not a statistical association between beta and return. Again, the statistical conclusions are consistent with previous studies which find no evidence of a statistical association between beta and average monthly returns (Bollen, 2010; Chaudhary, 2016).

Table 15

Correlation Analysis Statistics for Beta Category and Average Monthly Returns

Correlations

		Beta Category (High 3, Strong 2, Low 1)	2016-2018 Avg. Monthly Return
Beta Category (High 3, Strong 2, Low 1)	Pearson Correlation	1	-.087
	Sig. (2-tailed)		.412
	N	92	92
2016-2018 Avg. Monthly Return	Pearson Correlation	-.087	1
	Sig. (2-tailed)	.412	
	N	92	92

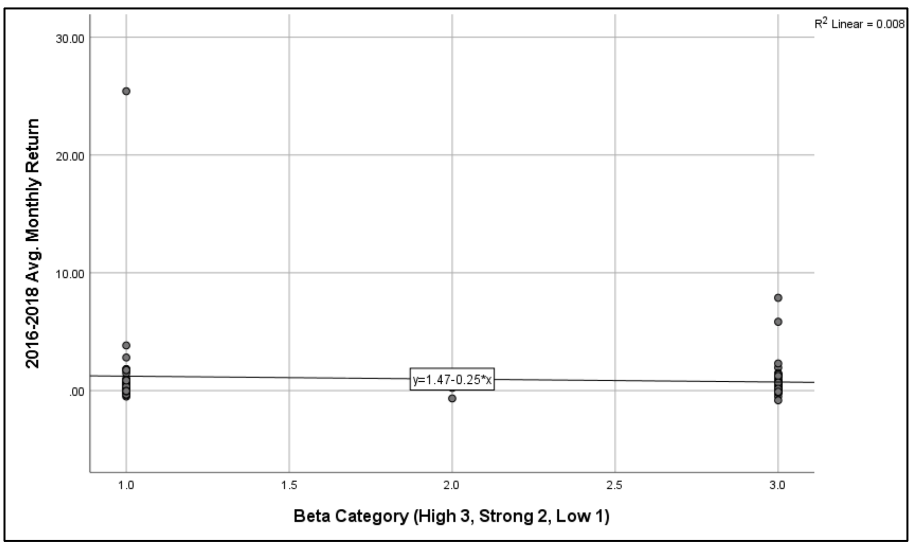


Figure 6. Scatterplot for beta category and average monthly returns

Hypothesis 4. For research question 3, the researcher compared the difference between average returns for each beta category and the average returns from the 11 GICS classifications. The research question is as follows:

RQ3: Is beta a better indicator of risk or excess returns for the eleven industry sector stocks listed in the S&P 100 index compared to the S&P 500 index as a benchmark?

The subsequent hypotheses compared the difference between the three beta categories and average monthly returns of the S&P 100.

H4: There is a statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the 11 Global Industry Classification Standard (GICS) stocks in the S&P 100.

H_o4: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the 11 Global Industry Classification Standard (GICS) stocks in the S&P 100.

H_o4a: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the energy sector stocks in the S&P 100.

H_o4_a: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the materials sector stocks in the S&P 100.

H_o4_b: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the industrials sector stocks in the S&P 100.

H_o4_c: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the consumer discretionary sector stocks in the S&P 100.

H_o4_d: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the consumer staples sector stocks in the S&P 100.

H_o4_e: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the health care sector stocks in the S&P 100.

H_o4_f: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the financial sector stocks in the S&P 100.

H_o4_g: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the information technology sector stocks in the S&P 100.

H_o4_h: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the telecommunications services sector stocks in the S&P 100.

H_o4_i: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the utilities sector stocks in the S&P 100.

H_o4_j: There is no statistically significant difference between average monthly returns for S&P 100 constituent stocks in the three beta categories (low, strong, & high) and average monthly returns for the real estate sector stocks in the S&P 100.

Table 16 and 17 contains the descriptive statistics for industry sector and average returns. The descriptive statistics also contain the means to be compared. Table 18 provides the Levene's test to check the assumption that the variance between industry sector and average returns. Industry sector was significant at $p = 0.00$ and industry sector average returns was significant $p = 0.02$. Average monthly returns for the S&P 100 were not significant at $p = 0.38$.

Table 16

Descriptive Statistics for Industry Sector and Average Monthly Returns

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
Industry Sector	Low	40	6.03	2.293	.362	5.29	6.76	1	11
	Strong	2	6.50	.707	.500	.15	12.85	6	7
	High	50	4.94	2.888	.408	4.12	5.76	1	9
	Total	92	5.45	2.658	.277	4.90	6.00	1	11
2016-2018 Avg. Monthly Return	Low	40	1.2542	4.01519	.63486	-.0299	2.5383	-.51	25.42
	Strong	2	-.2218	.62808	.44412	-5.8650	5.4213	-.67	.22
	High	50	.7498	1.41531	.20015	.3476	1.1520	-.83	7.88
	Total	92	.9480	2.84343	.29645	.3591	1.5369	-.83	25.42
Industry Sector Avg. Returns	Low	40	1.1055	1.42584	.22545	.6495	1.5615	-.02	4.30
	Strong	2	.6500	.07071	.05000	.0147	1.2853	.60	.70
	High	50	.8340	.70133	.09918	.6347	1.0333	.01	4.30
	Total	92	.9480	1.07527	.11210	.7254	1.1707	-.02	4.30

Table 17

Descriptive Statistics for Industry Sector, Average Monthly Returns, & Beta Category

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
2016-2018 Avg. Monthly Return	1	9	.1241	.39433	.13144	-.1790	.4272	-.20	.87
	2	6	.7531	.55434	.22631	.1713	1.3348	.16	1.48
	3	12	1.4614	1.57046	.45335	.4636	2.4592	-.50	5.84
	4	7	4.3036	9.33902	3.52982	-4.3336	12.9407	-.06	25.42
	5	9	.0087	.34567	.11522	-.2570	.2744	-.51	.51
	6	12	.7045	1.17750	.33992	-.0437	1.4526	-.67	3.83
	7	14	.5968	.73473	.19636	.1726	1.0210	.00	2.81
	8	12	1.2108	2.17796	.62872	-.1730	2.5946	-.10	7.88
	9	6	.1263	.52061	.21254	-.4200	.6727	-.83	.61
	10	4	.4419	.27478	.13739	.0047	.8792	.04	.67
	11	1	-.0241	.	.	.	.	-.02	-.02
	Total	92	.9480	2.84343	.29645	.3591	1.5369	-.83	25.42
Beta Category (High 3, Strong 2, Low 1)	1	9	2.78	.667	.222	2.27	3.29	1	3
	2	6	3.00	.000	.000	3.00	3.00	3	3
	3	12	2.50	.905	.261	1.93	3.07	1	3
	4	7	1.29	.756	.286	.59	1.98	1	3
	5	9	1.22	.667	.222	.71	1.73	1	3
	6	12	1.25	.622	.179	.86	1.64	1	3
	7	14	2.64	.745	.199	2.21	3.07	1	3
	8	12	2.50	.905	.261	1.93	3.07	1	3
	9	6	2.33	1.033	.422	1.25	3.42	1	3
	10	4	1.00	.000	.000	1.00	1.00	1	1
	11	1	1.00	.	.	.	.	1	1
	Total	92	2.11	.988	.103	1.90	2.31	1	3

Table 18

Test of Homogeneity of Variances between Industry Sector and Average Monthly Returns

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Industry Sector	Based on Mean	9.350	2	89	.000
	Based on Median	8.301	2	89	.000
	Based on Median and with adjusted df	8.301	2	81.022	.001
	Based on trimmed mean	9.395	2	89	.000
2016-2018 Avg. Monthly Return	Based on Mean	.977	2	89	.380
	Based on Median	.406	2	89	.667
	Based on Median and with adjusted df	.406	2	49.333	.668
	Based on trimmed mean	.421	2	89	.658
Industry Sector Avg. Returns	Based on Mean	6.492	2	89	.002
	Based on Median	2.583	2	89	.081
	Based on Median and with adjusted df	2.583	2	57.068	.084
	Based on trimmed mean	5.201	2	89	.007

The researcher again used a One-Way ANOVA to compare the difference between two or more independent groups with the dependent variable (Morgan et al., 2011). As previously stated, statisticians and researchers test for the assumption of the homogeneity of variance using Levene's test. When the value of the statistical significance in Levene's test is less than .05, then the assumption is violated. This is counter to most statistics because Levene's actually tests to see whether the means of each group are similar. If they are similar, then it means that there is no homogeneity of variance, which is a requirement for this inferential statistic.

Table 19 contains the ANOVA table for industry sector and average monthly returns. The table is divided into between-groups effects (due to the model or experimental effect) and within-group effects (systematic variation in the data). The sum of squares for the model equals 8.45 for average returns and equals 28.43 for the industry sector while the degrees of freedom are equal to 2. The test of whether the group means are the same is represented by the *F*- ratio for the between groups. The value for this ratio is .52 for average returns and a ratio of 2.1.for industry sector.

For average monthly returns, there is a probability of .60 that an *F*- ratio of this size would occur if there was no effect (or would occur by chance). As the critical cut off point of 0.05 was utilized as a criterion of statistical significance, the output of the analysis fails to reject the null hypothesis that there was no statistically significant effect of beta category on return. The findings are consistent with prior research from Terregrossa and Eraslan (2016) that found no systematic relationship between returns and beta.

$F(2,89) = .52$, $p. > .05$ (= .60)

For the industry sector output, there is a probability of .13 that an *F*- ratio of this size would occur if there was no effect (or would occur by chance). As the critical cut off point of

0.05 was utilized as a criterion of statistical significance, the output of the analysis fails to reject the null hypothesis that there was no statistically significant effect of beta category on industry return. Those findings are consistent with prior research of industry sectors from McNevin and Nix (2018) which found no significance in beta to fully identify systematic risk. *Figure 7* is a line graph of average monthly returns based on industry sector which shows the Consumer Discretionary sector with the highest average return.

$F(2,89) = 2.1$, $p. > .05$ ($= .13$)

Table 19

Analysis of Variance between Industry Sector and Average Monthly Returns

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Industry Sector	Between Groups	28.433	2	14.217	2.060	.134
	Within Groups	614.295	89	6.902		
	Total	642.728	91			
2016-2018 Avg. Monthly Return	Between Groups	8.452	2	4.226	.517	.598
	Within Groups	727.294	89	8.172		
	Total	735.746	91			
Industry Sector Avg. Returns	Between Groups	1.820	2	.910	.783	.460
	Within Groups	103.395	89	1.162		
	Total	105.214	91			

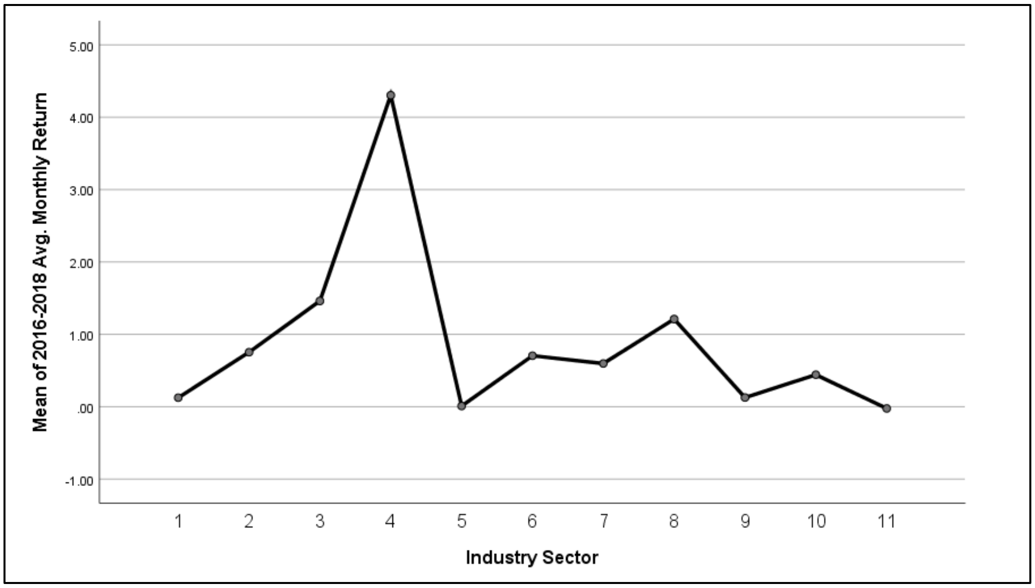


Figure 7. Line graph of average monthly returns by industry sector

Summary of the findings. The initial correlation analysis did not show statistically significant results, leading the researcher to fail to reject the null hypothesis for each research question, in that beta was an indicator or predictor of average monthly returns. While prior studies (Bilinski & Lyssimachou, 2014; Bornholt, 2013; Cai, Clacher, & Keasey, 2013; Fama & French, 1992; Moosa, 2013) challenged the flaws found in beta to predict average returns, this study confirms those anomalies found in beta. Banz (1981) identified the size effect and how this could influence relationship between beta and returns. In contrasting the results of this study to prior findings, beta was not a predictor of returns for stocks listed in the S&P 100.

The descriptive statistics show stocks listed in the S&P 100 had a higher mean for average returns in the low beta category compared to the strong or high beta category. This is consistent with the beta anomaly, which suggests low beta stocks outperform high beta stocks even though statistically an association or difference between beta and average returns was not warranted (Black, 1993; Bornholt, 2013; Fama & MacBeth, 1973; Johnstone, 2013).

Application to Professional Practice

The CAPM, and more importantly to this study the CAPM beta, is at the center of accounting and financial research, embraced by practitioners to calculate everything from cost of capital for budgeting to stock performance (Bilinski & Lyssimachou, 2014). Researchers have continued to test beta against other variables in an effort to explain why such variance occurs in beta (Fama & French, 1992). Beta anomalies, such as low beta stocks outperforming high beta stocks, have created a beta puzzle requiring the CAPM to be considered useful but still lacking credibility in addressing risk (Elmiger & Elmiger, 2018).

The findings of from this study are important to further the discussion around mitigating risk while increasing average returns. The study addressed gaps in the literature, which did not focus on index stocks or industrial classifications when studying whether the beta association creates a difference in average returns. The study built on previous research (Bollen, 2010; Chaudhary, 2016, Terregrossa & Erasian, 2016; Theriou et al., 2010) that produced variability in average returns for different stocks and from different portfolios that low (high) risk stocks should produce lower (higher) returns.

Due to investors' responsibility to manage their portfolios and more importantly, fund performance through the mitigation of risk, the application of risk management strategies are crucial for making informed decisions regarding the buying and selling of stocks (Bilinski & Lyssimachou, 2014). Terregrossa and Erasian (2016) concluded no systematic relationship existed between beta and portfolio returns, which was in contradiction to the belief a relationship would be present for portfolios. Using Turkish stocks to create portfolios to test the predictability of beta and returns, Terregrossa and Erasian found no conditional relationship between beta and returns.

Chaudhary (2016) used the same methodology to test beta and returns for Indian and US stocks. Theriou et al. (2010), using similar methods, employed the same portfolio creation and testing for stocks in the Athens stock market. Again, no statistical evidence was found to support beta and returns. The findings are consistent with the results of this study, which found no statistical significance between beta and average monthly returns for stocks listed in the S&P 100.

The findings for this study failed to reject the null hypothesis for each of the research questions as there was no statistical significance linkage to average returns, beta category, or industry sector. The lack of significance is important in that it continues to highlight the varying results researchers find when testing beta against average returns and using beta as a risk control (Bilinski & Lyssimachou, 2014). The lack of statistical significance highlights and lends consideration to the role of chance in predicting returns (Morgan et al., 2011).

Unlike the previous studies mentioned, a weak association between beta and returns were observed conditionally for Bilinski and Lyssimachou (2014). Bilinski and Lyssimachou found that beta was an indicator of large positive or large negative returns, which was not confirmed in this study. Unlike this study, Bilinski and Lyssimachou employed logistic regression models to show beta clustered in the tails of cross-sectional returns. Their sample size was considerably larger, which could account for the varying results found in this study. Other researchers have found a similar relationship between risk and returns, specifically to the S&P 100. Kanas (2012) implied a strong relationship between risk and returns for stocks in the S&P 100, however the risk was defined by the implied volatility index and not beta, which was not used in this study. While some researchers have found a correlation between risk and return, this study adds to the questions surrounding beta to predict returns.

The results are applicable to the field of finance and accounting cognate due to expanded discussion around beta anomalies inherent in individual stocks and those used to create portfolios. This study addressed the risk/return relationship and highlighted the beta puzzle that continues to plague investors. The beta puzzle observed in this study found that low beta stocks had higher returns on average than strong or high beta stocks in the S&P 100. This goes against the expected prediction of beta and average returns.

Living in a fallen society, the current study highlights the need for stewardship in the resources God has granted. While we can hedge against risk through diversification or other risk mitigating factors, it is clear investors should continue to use their own due diligence when building portfolios. Proverbs 13:11 states “wealth gained hastily will dwindle, but whoever gathers little by little will increase it.” Deuteronomy 8:18 states “you shall remember the Lord your God, for it is He who gives you power to get wealth, that He may confirm His covenant that He swore to your fathers, as it is this day.” The current study shows that while beta may not be the best indicator of risk, accumulating wealth is contingent on the blessing of God. He will provide and this provision comes with a responsibility to be a good steward of His blessings.

This study highlights the inability to control risk for investment purposes and the need to mitigate risk through research and historical data. As Christian leaders in business, we to are called to be stewards of resources given to us; not to use in our glory but to God’s glory. This study adds to the existing literature, which continues to ask more questions around the suitability of beta for risk prediction. As followers of Christ, we should adhere to the results in that controlling risk is outside of our control. Prayer and Godly council on how to use the resources God has given you are ways to mitigate the risk you perceive in portfolio creation and investing in the stock market. There are Christian based investors who create portfolios based on biblical principles.

Recommendations for Action

The purpose of this quantitative correlational study was to examine the relationship between beta and risk using the CAPM and equities from the S&P 100. The null hypothesis for RQ1 tested whether there was a statistically significant difference between the benchmark and the average monthly returns for the three beta categories. The null hypothesis for RQ2 tested the statistically significance association between average monthly returns and beta and showed it did not have a statistically significant association between beta and stocks in the S&P 100. After correlational analysis, the null hypothesis was not rejected. The null hypothesis for RQ3 tested whether there was a statistically significant difference between average monthly returns for the three beta categories compared to the 11 Global Industry Classification Standard. The results of the correlational analysis failed to reject the null hypotheses, meaning there is not a statistically significant difference between the three beta categories and average monthly returns for stocks in the S&P 100 compared to the benchmark (S&P 500) or industrial classification. The findings have several implications to the finance/accounting profession.

The first recommendation for action, regarding the use of beta category to compare the difference between average monthly returns and the benchmark, would be for investors and those creating an investment management strategy to use diversification to mitigate risk. The difference between the benchmark and average returns in the three beta categories did not have statistical significance difference at the *p* value, meaning the results could be due to chance. Investors should employ their diversification strategy by using a blended variety of high and low beta stocks across the industry classification system when building portfolios. Use 10 to 30 stocks when building a portfolio and ensure you spend time researching the historical results. Use a longer time horizon when deciding on your holding strategy and the historical returns from individual stocks.

While other researchers have found mixed results using beta as a risk control (Bollen, 2010; Bilinski & Lyssimachou, 2014; Fama & French, 1992; Fama & MacBeth, 1972) this study only adds to the beta puzzle. Typically, high (low) beta stocks produce higher (lower) returns. While beta is still the predominant risk indicator used by investors, the findings showed that beta category had no difference in average monthly returns. Due to the lack of a statistically significant difference between beta category and average returns against the benchmark, it is recommended that investors continue to use caution when using beta as a straight-line risk indicator to create portfolios only comprised of stocks in the S&P 100. Investors should continue to use a diversification strategy for portfolio creation and to use a blend of high and low stocks to hedge against risk. While a statistically significant difference between average monthly returns and beta category was not observed for stocks listed in the S&P 100, there was statistical significance between the association of average monthly returns and beta in general.

The second recommendation for action would be to create an investment management strategy using other risk indicators such as conditional betas or the volatility index as a risk indicator for stocks comprising the S&P 100. The association between beta and average monthly returns showed a negative correlation. The negative association between beta and average monthly returns for stocks in the S&P 100 led to the failure to rejection of the null hypothesis. The findings are consistent with prior researchers (Chaudhary, 2016, Terregrossa & Erasian, 2016; Theriou et al., 2010) that found beta and average monthly returns are not correlated. While a weak association has been found with beta, this study and other indicate investors should still use caution when using beta to create portfolios. When using beta as a risk indicator, use at least 5 years of historical returns to create beta. Most online resources use 5 years for beta calculations. For portfolio creation, the more data available for portfolio creation provides a more granular view of stock performance and accounts for market volatility. The hope is an investment management strategy will continue to use a variety of risk indicators for predications of average monthly return.

The final recommendation for action would be for investors and those creating an investment management strategy to not use beta category and industry sector for average monthly returns for stocks listed in the S&P 100. The difference between average monthly returns and the three beta categories compared to the eleven-industry sector was not statistically significant. Through correlational analysis the null hypothesis for RQ3 was not rejected. While there was not a difference between average monthly returns for the three beta categories and industry sectors, it is recommended that investors not use industry sector and beta categories alone to create portfolios.

This study has implications for investors, financial/accounting practitioners, and investment strategy managers. The results presented in this study confirm there is value in using beta as a risk indicator for investment strategy, but they do not completely answer the beta puzzle. The association of average monthly returns in the S&P 100 and beta confirmed beta as a risk indicator, however, beta category did not. It is important that financial practitioners continue to learn from research being conducted in the financial/accounting discipline. Thus, the researcher will seek out peer related journals in the fields of finance and accounting to publish the findings.

Recommendations for Further Study

The purpose of this study was to determine if there was a difference or association between beta and average returns for stocks listed in the S&P 100 when compared to the benchmark (S&P 500) and industrial classification. Throughout this study, the researcher sought to fill in gaps and to invigorate further discussion around using beta as risk control for accounting and finance research. While there is continued research into developing new conditional beta measures to validate the CAPM, there is one area that warrants further examination.

When forecasting beta, it is left to the researcher to determine the appropriate time horizon (2, 3, or 5 years). Cenesizoglu et al. (2016) tested many of the standard beta assumptions and found the Fama and MacBeth 5 year beta generated the most accurate beta forecast. However, other beta forecasting models have generated favorable results. Most stock and financial websites, such as Yahoo! Finance and Google Finance, use different betas with the same historical data. It was found that most beta calculations use the 3-year prediction approach, although prior research has found utilizing 5 years ahead produces a more accurate prediction. Future research should review beta forecasting models and determine the appropriate method to calculate beta based on the 24, 36, and 60 month horizon.

Another recommendation for future studies would be to focus on changing the beta model from a one factor model to a three factor model such as used by Fama and French (1993). The three factor model incorporates into the CAPM market risk or beta, small vs. big corporations, and book to market ratio. Using all three factors could provide a more robust and deeper understanding of risk for stocks in the S&P 100.

Other researchers could focus on incorporating a conditional beta approach for the S&P 100 by using a weighted average of three betas estimated through different research periods (Cenesizoglu & Reeves, 2018). The conditional beta method of Cenesizoglu and Reeves (2018) uses daily returns to calculate beta for short term components. It would be of interest to observe the variance in daily versus monthly returns for beta calculations.

Finally, it is recommended that future researchers use a different date range or a least a longer time horizon due to the financial crisis of 2008. The noise in the financial data is attributed to the financial crisis and could be smoothed out by using a time horizon of twenty years. Using data from 2000-2018 could be beneficial, capturing the years before and after the financial crisis. It would be useful to determine how influential the financial crisis skewed the current study.

Reflections

An important lesson learned through this process was to take care not to underestimate the data collection and organization prior to analysis. There is a host of websites available to access archival data. Most provide the data free of charge and available for downloading. While the researcher works with large amounts of data on a daily basis, organizing the data for statistical analysis was a new opportunity. Some preconceived confidence in working with data lead to delays in actual statistical analysis due to the data not being organized properly. Ensuring the data is uniform when downloading from multiple sites requires organizational techniques to enable a quality standard of data analysis. It is crucial to ensure a data organization plan is formulated on the front end before data is retrieved. The researcher had to fix issues in data organization, which was time consuming and delayed the research process.

Many times, throughout the research process there were roadblocks or challenges. As a working professional and doctoral student, creating a work-life-school balance can be difficult. Factored into the experience of the researcher, a career change and move across country created perhaps the greatest challenges to finish this project. The Bible provides many instances which were all tested and endured to persevere. James (1:12) states “blessed is the man who remains steadfast under trial, for when he has stood the test, he will receive the crown of life, which God has promised to those who love him.” Romans (5:3-5) “more than that, we rejoice in our sufferings, knowing that suffering produces endurance, and endurance produces character, and character produces hope, and hope does not put us to shame, because God's love has been poured into our hearts through the Holy Spirit who has been given to us.” In the end, the researcher found the most comfort in Matthew (24:13) “but the one who endures to the end will be saved.” Persevering throughout this process was at times challenging, but it was the continued support of God allowed this project to be completed.

Summary and Study Conclusions

The purpose of this quantitative correlational study is to examine the relationship between beta using the CAPM and equities from the S&P 100. The study was conducted using the average monthly returns from each constituent stock listed in the S&P 100 to determine if there was a difference or association between the benchmark (S&P 500) or industrial classification. The S&P 100 contains large blue chip companies which are considered some of the largest companies across multiple industry groups, and all companies in the S&P 100 are U.S. companies. The total population for this study was used as the basis of the sample.

The problem to be addressed was the beta anomaly, in which low beta stocks outperform high beta stocks, resulting in a situation in direct contradiction with the CAPM and with investor's expectations. The beta puzzle continued to be an issue in predicting market risk for portfolio creation and indicated low beta stocks outperform high beta stocks even with a higher pricing premium (Driessen, Maenhout, & Vilkov, 2009). While the total sample size of 92 was lower than anticipated due to delisting, it was sufficient to conduct an analysis at a < 0.05 confidence level.

The mean values for beta category (low, strong, & high) indicated that low beta average returns for the S&P 100 were larger, however, the statistical results showed no significance for beta category or average returns. The primary correlation led the researcher to fail to reject the null hypothesis. This study did not have a statistically significant difference between average monthly returns between the S&P 100 and benchmark and beta. There was an inverse relationship between average monthly returns in each beta category. The results are consistent with prior research in which beta was unable to predict average monthly returns. Therefore, the conclusion for this study is that there is no evidence to suggest that there is a difference or association between beta and average monthly returns for the S&P 100 stocks.

In closing, this study accomplished several objectives. Primarily, it added to the literature and closed the gap as to whether beta is a suitable market risk indicator for stocks comprising the S&P 100. Additionally, this study contributed to the accounting and finance discipline by improving the overall understanding of market risk and average monthly returns. Finally, this study was an incredible journey, not only to close the gap in the literature but to galvanize the resolve of the researcher to complete the DBA program at Liberty University so that I may be an instrument for Jesus Christ in fulfilling the Great Commission.

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Appendix A: S&P 100 Constituents

Appendix A includes all constituents in the S&P 100 as of January 1, 2010. The list includes the trade ticker, ISIN Code, and company name.

Ticker	**ISIN Code**	**Company Name**	**1/1/2010**
AA	US0138171014	Alcoa Inc.	X
AAPL	US0378331005	Apple Inc.	X
ABT	US0028241000	Abbott Laboratories	X
AEP	US0255371017	American Electric Power	X
ALL	US0200021014	Allstate Corp.	X
AMGN	US0311621009	Amgen Inc.	X
AMZN	US0231351067	Amazon.com Inc.	X
AVP	US0543031027	Avon Products	X
AXP	US0258161092	American Express Co	X
BA	US0970231058	Boeing Co.	X
BAC	US0605051046	Bank of America Corp.	X
BAX	US0718131099	Baxter International Inc.	X
BHI	US0572241075	Baker Hughes Inc.	X
BK	US0640581007	Bank of New York Mellon Corp	X
BMY	US1101221083	Bristol-Myers Squibb	X
BNI	US12189T1043	Burlington Northern	X
C	US1729674242	Citigroup Inc.	X
CAT	US1491231015	Caterpillar Inc.	X
CL	US1941621039	Colgate-Palmolive	X
CMCSA	US20030N1019	Comcast Corp. Class A Comm.	X
COF	US14040H1059	Capital One Financial	X
COP	US20825C1045	ConocoPhillips	X
COST	US22160K1051	Costco Co.	X
CPB	US1344291091	Campbell Soup	X
CSCO	US17275R1023	Cisco Systems	X
CVS	US1266501006	CVS Caremark Corp.	X
CVX	US1667641005	Chevron Corp.	X
DD	US2635341090	DuPont	X
DELL	US24702R1014	Dell, Inc.	X
DIS	US2546871060	The Walt Disney Co.	X
DWDP	US26078J1007	DowDuPont Inc.	X
DVN	US25179M1036	Devon Energy Corp.	X
EMC	US2686481027	EMC Corp.	X
ETR	US29364G1031	Entergy Corp.	X
EXC	US30161N1019	Exelon Corp.	X
F	US3453708600	Ford Motor	X

FCX	US35671D8570	Freeport-McMoRan Inc.	X
FDX	US31428X1063	FedEx Corp	X
FOXA	US90130A1016	Twenty-First Century Fox Inc. Class A	X
GD	US3695501086	General Dynamics	X
GE	US3696041033	General Electric	X
GILD	US3755581036	Gilead Sciences	X
GOOGL	US02079K3059	Alphabet Inc. Class A	X
GS	US38141G1040	Goldman Sachs Group	X
HAL	US4062161017	Halliburton Co.	X
HD	US4370761029	Home Depot	X
HNZ	US4230741039	H. J. Heinz Company	X
HON	US4385161066	Honeywell Int'l Inc.	X
HPQ	US40434L1052	Hewlett-Packard	X
HSH	US4325891095	Hillshire Brands Co	X
IBM	US4592001014	International Business Machines Co	X
INTC	US4581401001	Intel Corp.	X
JNJ	US4781601046	Johnson & Johnson	X
JPM	US46625H1005	JPMorgan Chase & Co.	X
KO	US1912161007	The Coca Cola Co.	X
LMT	US5398301094	Lockheed Martin Corp.	X
LOW	US5486611073	Lowe's Cos.	X
MA	US57636Q1040	MasterCard Inc.	X
MCD	US5801351017	McDonald's Corp.	X
MDLZ	US6092071058	Mondelez Int'l	X
MDT	IE00BTN1Y115	Medtronic Inc.	X
MET	US59156R1086	MetLife Inc.	X
MMM	US88579Y1010	3M Company	X
MO	US02209S1033	Altria Group Inc.	X
MON	US61166W1018	Monsanto Co.	X
MRK	US58933Y1055	Merck & Co.	X
MS	US6174464486	Morgan Stanley	X
MSFT	US5949181045	Microsoft Corp.	X
NKE	US6541061031	Nike, Inc.	X
NOV	US6370711011	National Oilwell Varco Inc.	X
NSC	US6558441084	Norfolk Southern Corp.	X
NYX	US6294911010	NYSE Euronext	X
ORCL	US68389X1054	Oracle Corp.	X
OXY	US6745991058	Occidental Petroleum	X
PEP	US7134481081	PepsiCo Inc.	X
PFE	US7170811035	Pfizer Inc.	X
PG	US7427181091	Procter & Gamble	X

PM	US7181721090	Philip Morris International	X
QCOM	US7475251036	Qualcomm, Inc.	X
RF	US7591EP1005	Regions Financial Corp.	X
RTN	US7551115071	Raytheon Co.	X
S	US8520611000	Sprint Corp.	X
SLB	AN8068571086	Schlumberger Ltd.	X
SO	US8425871071	Southern Co.	X
T	US00206R1023	AT&T Inc.	X
TGT	US87612E1064	Target Corp.	X
TWX	US8873173038	Time Warner Inc.	X
TXN	US8825081040	Texas Instruments	X
UNH	US91324P1021	United Health Group Inc.	X
UPS	US9113121068	United Parcel Service Inc.	X
USB	US9029733048	U.S. Bancorp	X
UTX	US9130171096	United Technologies	X
VZ	US92343V1044	Verizon Communications	X
WBA	US9314271084	Walgreens Boots Alliance	X
WFC	US9497461015	Wells Fargo	X
WMB	US9694571004	Williams Cos.	X
WMT	US9311421039	Wal-Mart Stores	X
WY	US9621661043	Weyerhaeuser Corp.	X
XOM	US30231G1022	Exxon Mobil Corp.	X
XRX	US9841211033	Xerox Corp.	X