The International Journal of Business and Finance Research
Vol. 13, No. 2, 2019, pp. 45-69
ISSN: 1931-0269 (print)
ISSN: 2157-0698 (online)

www.theIBFR.com

ASSET PRICING MODEL ESTIMATION ERRORS DURING RATIONAL AND IRRATIONAL INVESTOR BEHAVIOR PERIODS

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ABSTRACT

This paper examines the prediction that human behavior changes the outcome of market predictability, indicated by a difference in asset pricing model estimated prediction error, calculated using the Sharpe ratio, Jensen's alpha, and the Treynor measure for publicly traded firms in the consumer discretionary and consumer staples sectors. Applying a series of independent t-tests to mean comparisons of these measures ultimately provided mixed results, demonstrating a statistically significant difference only with Jensen's alpha and the Sharpe ratio in both sectors. This indicates a need for extra caution for asset pricing model use under potentially irrational periods.

JEL: G12, G41

KEYWORDS: Asset Pricing, Behavioral Finance, Irrationality, Beta

INTRODUCTION

Asset pricing models are a major tool in investor pricing, serving as a mechanism to measure the undiversifiable systematic risk of a potential investment. However, the theory of behavioral finance challenges the applicability of the models' assumptions. According to behavioral finance theory, irrational investors create inaccuracies in the traditional paradigm that all investors are rational and risk-averse (Hillson, Sobehart, Ursachi, and Riedel, 2014). Since certain environmental conditions tend to generate greater investor irrationality (McConnell, Böcker, and Ong, 2014), this research examined historical data regarding model accuracy and tested for differences in average accuracy when those environmental conditions did and did not exist.

The main challenge that behavioral finance theory offers to asset pricing is that neither individuals nor groups operate in a homogenous, predictable manner and therefore financial applications must consider potential psychological aspects (Thaler, 2015). These aspects counter the assumption of expected behavior that exists across the field of finance. The premise is that investors act in a manner established by a desire to maximize their personal expected utility functions (Sharpe, 1964). Behavioral finance theory challenges this premise, noting that investors are neither totally rational nor symmetric in their utility (Horvath and Sinha, 2017). Financial models and investment strategies rely on observed history. Under an assumption of rationality, people making their own personal best choices incorporate this historical information, then update their choices as they learn new information (Evstigneev, Schenk-Hoppé, and Ziemba, 2013). However, financial models are often wrong (Goss, 2017), and behavioral finance theory attempts to explain why the traditional paradigm of homogenous, rational, utility-maximizing investor behavior is inaccurate (Hillson et al., 2014). This, in turn, leads to the development of investment models that identify and incorporate these irrational actors.

The purpose of this quantitative, non-experimental, causal-comparative study was to test behavioral finance theory, which predicts that investors, not being rational as asset pricing models assume, will make decisions that result in differences from what the models estimate (Blitz, Falkenstein, van Vliet, and Bollen, 2015). If behavioral finance theory is accurate, then human behavior changes the outcome of market predictability, which a difference in estimation error measurements could indicate (Hillson et al., 2014). The research sought to determine if there is a significant difference in the mean error of asset pricing model estimated prediction given historical prices during periods of extended market loss and mean error for periods in which the market had gains or smaller periods of loss. Throughout this research, extended market loss referred to two or more consecutive months between 1994 and 2016 when the overall market index fell (García, 2013). The study examined these periods for firms categorized as staple goods firms and firms categorized as discretionary goods firms, as previous research indicated that these sectors display a differential role in investor behavior (Walkshäusl, 2014). This empirical test thus attempted to validate inaccuracies in the models with respect to the challenges of behavioral finance theory.

The theoretical implication of this research for business practitioners, specifically within the field of finance, is the provision of empirical evidence either supporting or contradicting behavioral finance theory as it applies to capital decision making. A fundamental piece of future behavioral finance research is discovering what causes anomalies between anticipated and actual returns (Mendes-da-Silva, da Costa, Ayres Barros, Rocha Armada, and Norvilitis, 2015). The importance of this research's impact goes beyond just the individual investor or investment firm, since, from the behavioral perspective, it is ultimately individuals or groups of people and not systems that make investment management decisions (Hillson et al., 2014). Therefore, behavioral finance theory emphasizes that since homogeneity and predictability are not realistic, financial models need to consider potential psychological aspects (Thaler, 2015).

The practical implications of this research apply to those practitioners who make use of asset pricing models. Through the empirical results of testing, this research provides evidence as to whether users can continue having trust in these models, or whether, in accordance with behavioral finance theory, there are times when the models are of questionable utility. Critics of these models, especially the capital asset pricing model (CAPM) point out that the models' assumptions are unrealistic, thereby making these models less robust than their proponents claim (Dempsey, 2013). However, the models remain widely in use, in part because of simplicity. As many as three-fourths of all corporations and regulatory agencies use the CAPM or related models in investment decisions (Brown and Walter, 2013) and it remains one of the most popular means to calculate asset prices (French, 2018). A challenge to the model, therefore, must not only demonstrate a universal or specific environment where the model is inaccurate, but must also demonstrate the extent to which there is a problem (Johnstone, 2013). If a researcher can distinguish how much of an anomaly can be explained by a specific behavioral factor, then investors and regulatory bodies could react more rapidly and appropriately in the face of what might initially appear to be an irrational market (Blasco, Corredor, and Ferreruela, 2012). This means that any research comparing behavioral finance theory with asset pricing models must show both that the behavioral model is correct and that the traditional model is inaccurate to a degree that matters to the end user.

According to behavioral finance theory, investors ultimately make decisions affected by psychological stimuli, and thus do not consistently function within the confines of the assumption of rational investing required by the asset pricing models (Brzezicka and Wisniewski, 2014). However, while a significant amount of behavioral finance research has focused on demonstrating the presence of such psychological factors, the majority of this research did not address whether there had been any actual impact on the model outcomes (Michaud, 2013). Thus, while research had verified that the model could produce anomalous results and that under certain market conditions investors would make irrational decisions (Subrahmanyam, 2013), researchers have not conducted an empirical examination linking these two circumstances.

Thus, to address this gap in the scholarly literature, this study sought to determine if there was a significant difference in three major forms of asset pricing model estimated prediction error measurement during periods of extended market loss and mean error for periods in which the market had gains or smaller periods of loss. Further, the study examined these periods for staple goods firms and discretionary goods firms. In this manner, the study attempted to validate inaccuracies in asset pricing models with respect to the challenges of behavioral finance.

The remaining sections of this paper provide more detail and analysis. The literature review describes a brief history of asset pricing models and their criticisms as well as the impact of behavioral finance theory on these models. A review of the methodology of the study follows, including an examination of the target population, data collection procedures, and data analysis methods. The methodology is followed by the results of the study, finishing with concluding remarks, references, and a short biography of the authors.

LITERATURE REVIEW

In a seminal description of behavioral finance theory, Barberis and Thaler (2003) challenge the premise that individuals and groups operate in a homogenous, predictable manner. In part, this simplifying assumption exists due to the extreme difficulty in modeling a system wherein each participant is not fully rational and therefore not predictable. However, empirical evidence from past research indicates the existence of those cognitive biases that Barberis and Thaler proposed (de Sousa Barros and dos Santos Felipe, 2015). For example, research has shown that during times of economic upheaval, especially negative upheaval, investors will react to news differently than they react to similar news in a stable economy (Hillson et al., 2014). Additionally, investors appear to change investment behavior dependent upon the investment type or market segment within which the investment lies (Walkshäusl, 2014). These anomalous results not only contradict the standard neoclassical macroeconomic theory, but also fall outside other heterodox economic schools of thought such as Austrian, Marxist, or post-Keynesian (Hands, 2014).

From an empirical standpoint, testing the applicability of the asset pricing models means comparing the ex-ante decisions investors would make with actual market results. Thus, the researcher is seeking a determination of a significant difference between predicted asset prices and those that actually occur. These differences produce estimated prediction errors due to the linear relationship between beta and portfolio return (Kahn and Lemmon, 2016). Alternatively, a finding that does not demonstrate a linear relationship would indicate flawed assumptions and a reason for potentially rejecting a model (Fama and French, 1996, 2004). However, it is important to note that such testing does not indicate the reason for failure, only that failure exists. Black, Jensen, and Scholes (1972) developed a seminal procedure that applied a cross-sectional methodology to reduce the problem of bias. This bias existed due to measurement errors in the risk-free and market return rates, factors inherent in attempting to make time-series data fit a static model (Roll, 1969; Alonso, Bastos and García-Martos, 2018). The success in accomplishing this bias reduction led to the Black-Jensen-Scholes process becoming the benchmark by which researchers test asset pricing models (Pesaran and Yamagata, 2012).

A researcher could thus use acceptance or rejection of an empirical test for comparison based on some form of changeable factor. An acceptance of the model when a factor is in one state and rejection in another state, ceteris paribus, would provide a theoretical justification for the existence of influence in that factor (Kothari, Shanken, and Sloan, 1995). For example, Bartram, Brown, and Stulz (2012) compared U.S. stock volatility to global stock volatility and found that U.S. stocks had greater idiosyncratic risk. By then analyzing the potential factors for this higher level of risk, they hypothesized that the volatility results were due to greater entrepreneurship in U.S. firms. Contrarily, Dellavigna and Pollet (2013) evaluated the differences between capital budgeting decisions and market timing decisions. In this case, results indicated no difference in the model, and therefore they were unable to determine whether either factor had a greater impact on actual investment decisions.

As researchers conducted more studies on investor behavior, they have been able to identify additional areas where investors operate in a manner contrary to the traditional rational thought (de Sousa Barros and dos Santos Felipe, 2015; Korniotis and Kumar, 2013; Mitroi and Oproiu, 2014). This study sought to examine asset pricing models during a time that previous behavioral finance research identified as a period in which investor behavior is outside the assumed norm (García, 2013). Thus, if behavioral finance theory is correct, the psychological factors during these periods would counter the efficacy of the models (McConnell et al., 2014). Examining the actual accuracy of the asset pricing models will serve to help confirm or refute the theory regarding its impact on the models themselves.

The rationale behind examining asset pricing through the lens of behavioral finance theory is that behavioral finance unifies a number of different fields in the effort to explain anomalies in the market (Brzezicka and Wisniewski, 2014). Thus, research along these lines combines traditional financial methods, including econometric and statistical approaches, with the areas of psychology, sociology, and neurobiology (Mendes-da-Silva et al., 2015). This can lead to a theoretical approach from a nonfinancial field becoming the basis for an explanation of the discrepancies between model and reality, as well as the nature of these discrepancies (Brzezicka and Wisniewski, 2014). A seminal example of this was the examination by Lee, Shleifer, and Thaler (1991) of a long-standing puzzle in closed-end funds. Their research examined the anomaly wherein closed-end funds did not sell at prices that equated to the market value of the assets contained within the fund. Traditional financial factor analysis, including tax liability and asset illiquidity, explained some of the existing anomalies, but not a significant portion. However, the inclusion of a psychological component, specifically investor reluctance to change their behavior in defiance of what would appear logical, also known as sentiment, potentially explained the deviation in expected assets that financial fundamentals could not (Lee et al., 1991). Continued examination of areas not traditionally linked to finance has increased the dynamic nature of financial research, to include research on asset pricing (Brzezicka and Wisniewski, 2014).

Asset pricing models are a fundamental area of finance in both academic research and practical application (Bilinski and Lyssimachou, 2014). Sharpe published the capital asset pricing model in 1964, expanding on Markowitz's mean-variance approach to portfolio optimization with utility in predicting investor behavior under conditions of risk. In the five decades since, both proponents and critics of the model have agreed that practitioners widely accept and use the model (Smith and Walsh, 2013). The model first gained wide usage due to its simplicity and positivist orientation, which made it an attractive model to its adherents (Ross, 1978). Following its publication, it also garnered wide acceptance because the model was intuitive concerning predictions on risk and return relationships (Fama and French, 2004).

When conducting a study on asset pricing models, particularly with an empirical examination, the researcher has a vast array of previous research in the field to draw upon. On the other hand, due to continued use despite theoretical challenges, empirical analysis of certain aspects of asset pricing models remains relatively sparse (Blasco et al., 2012). By analyzing the successes, pitfalls, and lacks in previous work, researchers can select the most appropriate approach for their current study. Whether offering additional proof of the model's positive or negative attributes or using the model to test the pragmatism of a specific theory, researchers must ensure that they fully explain the models' construct and research methodology.

Critics of asset pricing models point out that because the assumptions are unrealistic, then the models are less robust than supporters of those models would claim (Dempsey, 2013). In particular, detractors have attacked the assumptions of homogeneity in investor expectations, the prohibition against portfolio rebalancing, and the assumption of rational investors (Hillson et al., 2014). Therefore, researchers have sought to identify those factors that have an influence on investors, while understanding that there is no all-inclusive list of factors or their relative impact (Geambaşu, Şova, Jianu and Geambaşu, 2013).

A summation of extant literature reveals a significant difference in approach dependent upon whether the focus of the research was on asset pricing models or on behavioral finance theory. Financial models and investment strategies rely on observed history (Evstigneev et al., 2013). Mathematical approaches examining the anomalies in asset pricing models tend to either make a subjective conclusion regarding the theoretical failure of the model (Dempsey, 2013) or try to combine a variety of factors with the random nature of stock prices to explain actual market behavior (Fontana, 2015). Behavioral finance articles tend to focus on descriptions of why the traditional paradigm is inaccurate (Hillson et al., 2014). These may be empirical in nature regarding identification of psychological traits, but not actually identification of a quantitative impact regarding the model.

Further research into behavioral finance theory and its relationship to asset pricing models depends upon a bridging of theory and applicability. Whether attempting to identify factors that should be included in a model, determining a better measurement methodology for those factors, or incorporating new algorithms and strategies for use of the model, there remains a balance tying theory and application (Geambaşu et al., 2014). The theoretical model must inherently make sense and meet the needs of the end-user (Hazan and Kale, 2015). This, in turn, may be dependent upon user ability to create their own linkages between proposed theory and explained results.

There are only a limited number of research improvement efforts that identify areas where mathematics linked the behavioral theoretical approach to model acceptance or rejection (Roa García, 2013). For example, advances in the understanding of Brownian motion have allowed models that, when empirically examined in hindsight, showed greater realism (Hazan and Kale, 2015). Even with known limitations, the challenges to asset pricing model applicability remain subject to serious debate (McConnell et al., 2014). Therefore, research into an area that potentially challenges the model must include logical linkages to the proposed factors affecting the model, including a solid theoretical background that specifically addresses the limitations of model assumptions (Hillson et al., 2014).

DATA AND METHODOLOGY

This research was a quantitative, non-experimental, causal-comparative secondary data study. Using monthly historical data allowed the calculation of estimated prediction errors. There are various methodologies for determining the prediction error deviation in asset pricing models, dependent upon the significance of volatility and normalcy in the population (Mistry and Shah, 2013). Therefore, the study included the calculations of the Sharpe ratio, Jensen’s alpha, and the Treynor measure. The calculations also required a proxy for the overall market and the risk-free rate as part of the error estimate calculations. For these proxies, the Russell 3000 index incorporates 98% of all U.S. securities for the overall market proxy, while the one-month U.S. Treasury bill served as proxy for the monthly risk-free rate, since it has demonstrated accuracy and appropriateness for time series comparisons of prediction error (Smith and Walsh, 2013). Additionally, the data required a census of all secondary data, specifically the monthly return, for publicly held U.S. stocks in the consumer staples and consumer discretionary sectors from 1994 through 2016.

Once the time-based prediction errors were calculated, they were categorized based on whether the period fell into an interval of extended market loss or not. In accordance with the predictions of behavioral finance theory, during these periods of extended loss, investors do not make rational investment decisions, and therefore asset pricing models should be less accurate (García, 2013). An independent t-test determined if a statistically significant difference existed between these two groups. The discovery of a statistically significant difference would lend credence to the potential causality of investor behavior influencing the utility of the models.

Although asset pricing models are used as a priori tools for assistance with investor decisions (Sharpe and Litterman, 2014), this study analyzed historical or ex-post data. This approach assumed that ex-post experiences reflected the a priori perceptions that a researcher could not measure in and of themselves (Barnham, 2015). Thus, while an experimental design may be preferable for determination of the linkage between irrational investor behavior and asset pricing, the non-experimental design was appropriate for the impact of the research required to demonstrate whether the theoretical effect of investor irrationality was, in fact, present (Reio, 2016). This type of ex-post evaluation is consistent with the positivist ontological premise of understanding reality objectively and systematically (du Toit and Mouton, 2013). Additionally, this type of research design was particularly appropriate for financial research, as it is often exceedingly difficult to conduct actual experiments with financial decision-making since there is little availability of either sampling or controlling extraneous data (Andrews, Higgins, Andrews, and Lalor, 2012).

The presence or absence of a difference in dependent variables based on groupings of the independent variable would provide empirical support for theoretical causation (Turner, Balmer, and Coverdale, 2013). An existing difference in estimated prediction error measurements for recessionary period equities and growth period equities would suggest that the independent variable influences the dependent variable. While a causal-comparative analysis cannot definitively demonstrate this relationship, it does offer anecdotal evidence. Therefore, model failure would lend credence to acceptance of behavioral finance theory's premise that violation of the capital asset pricing model's assumptions leads to greater model errors (Haneef, 2013).

The population for this research was the publicly traded firms identified by Standard & Poor's (S&P, 2016) as members of the Global Industry Classification Standard (GICS) consumer discretionary sector and consumer staples sector. Of the possible sectors comprising the U.S. equities market, these two sectors have demonstrated distinct differences in abnormal profits during periods of market disruption (Pesaran and Yamagata, 2012). Thus, this study could differentiate between firms likely to experience volatility affecting asset pricing models, namely the consumer discretionary firms, and those likely to remain stable even during disruptive periods, specifically in the consumer staples sector (Rostan and Rostan, 2012).

This population contained 122 firms, with 86 firms in the consumer discretionary sector and 36 in the consumer staples sector (S&P, 2016). Two firms with some data in the 2016 consumer discretionary sector were not included in this study. In the first case, Samsung Electronics Company, Ltd. acquired Harman International Industries Inc. (Tsang, 2016), thus conflating their data with information from the Korea Exchange, which was outside the scope of this study. The second excluded firm, Yum China Holdings, Inc. held their initial public offering in November 2016 (Little, 2016). Thus, Yum China Holdings did not have sufficient data to calculate the required prediction errors. A list of all firms included in the population is found in Appendix A.

The differentiation between staple and discretionary goods leads to some key differences in the financial data of the two sectors. Consumer staples stocks tend to have a lower volatility than consumer discretionary stocks (Rostan and Rostan, 2012). Additionally, stocks in the staples sector tend to have a lower beta than the market and less correlation to the overall market than discretionary sector stocks (Walkshäusl, 2014). From a rational perspective, then, the staple goods sector should be affected less by recessionary versus growth periods than the discretionary goods sector (Haneef, 2013), providing additional insight into the theoretical impact on asset pricing. The combination of these two sectors creates a diverse yet manageable population that is appropriate for the research design.

Although a typical causal-comparative analysis would use a representative random sampling of the population, this research instead made use of a census of the entire population, providing the most accurate measure of the population and avoiding sampling error (Chatha, Butt, and Tariq, 2013). The limited size of the overall population, comprising of only 126 total firms, along with the readily accessible nature of the required data from the population, overcomes the ordinary restraints that would lead a researcher to select sampling versus a census.

While the use of a census in our research eliminated the need for participant selection, as well as the possibility of sampling error, a census still has the potential pitfall of unreliable data and data sources (Callahan, 2017). The census consisted entirely of collecting secondary data from publicly available sources, which allowed for independent verification of data correctness, ensuring required fidelity (Lagarto, Delgado, Paulino, and Capelo, 2017). Historical stock information was available from databases such as Morningstar, Bloomberg, and YCharts, while Russell 3000 data came from FTSE and Treasury Bill data was obtained from the archives of the U.S. Federal Reserve. The dates for the census included all available data from the population from 1994 through 2016. These dates thus included all complete years from the establishment of the market proxy, the benchmark Russell 3000 Index, through the start of the study process. This ensured continuity of data while also ensuring the inclusion of numerous periods of market rise and decline across the population.

Although the census included all firms in the target population of publicly-traded consumer discretionary and consumer staple goods, it is worth noting that the specific firms in that population were selected based on the Global Industry Classification Standard (GICS) classification system. Financial analysis often uses industry classification to obtain contextual homogeneity, and researchers can choose from a number of possible classification schemes. The use of a classification scheme for population selection has an impact on the eventual application of the model, with the Fama and French (1997) algorithm for industry classification being appropriate for academically focused research with an emphasis on risk characteristics and the GICS industry classification being useful for investigating analyst behaviors (Bhojraj, Lee, and Oler, 2003). The market-oriented GICS system for differentiation is appropriate in this study because this classification method demonstrates more reliable industry groupings for financial analysis and research than other classification methods (Hrazdil and Scott, 2013). Since Standard and Poor's indexing uses the GICS classification (S&P, 2016), the S&P sector indexes dictated the actual population members. The use of these specific firms as the population also helped establish the definition of the market portfolio against which the individual firms were compared.

The market portfolio is the fully diversified return in proportion to market capitalization, which would thus be free from unsystematic risk, and from which individual assets deviate (Sharpe, 1964, Lo, 2016). A true market portfolio would represent an investment in every available asset in proportion to its value but there tends to be universal agreement that calculating the actual value, which would include equities, bonds, real estate, and more, is essentially impossible, both theoretically and empirically (Hands, 2014). Thus, a proxy is required for use in the model. Since neither research nor practice have identified proxies that are both universally accepted and practical (Chordia, Goyal, and Shanken, 2015), the selection of an appropriate proxy is an important part of the research design. A test of a specific factor, circumstance, or environment, such as the one in this research, can empirically use a market proxy that accurately represents the financial and behavioral ex-ante choices, which is to say the available information and environment prior to actually making any market selections that the investor has (Partington, 2013). Since the proxy needed to represent the research market as a whole, the monthly Russell 3000 Index serves as the market proxy in this study. This index encompassed the largest portion of available U.S. publicly traded equities, and thus reflected the overall market for the industry sectors (Partington, 2013). The Russell 3000 Index not only includes all of the consumer discretionary and consumer staples sectors but also represents over 98% of the overall U.S. publicly traded securities market (FTSE, 2016). Selection of the Russell 3000 as the proxy also drove a starting point for census collection, since the Index began in 1994 (FTSE, 2016). This established part of the timing requirements for the study.

Calculation of consecutive month loss required comparing each Russell 3000 Index end of month value to the value for the previous two months. Kothari, Shanken, and Sloan (1995) found that the use of monthly data was appropriate since asset pricing model measurements are more accurate when using monthly intervals than daily intervals. While there has been some debate regarding this claim, the use of monthly data has become the academic standard (Nyangara, Nyangara, Ndlovu, and Tyavambiza, 2016). Limiting the census to monthly data over the 23-year period of 1994 through 2016 meant 276 date periods, sufficient to generate a statistically useful but not unmanageable 48 months of consecutive loss and 226 months of gain or inconsecutive loss (FTSE, 2016). These periods represent the independent variable of extended negative or positive growth.

The operational definition of extended negative market growth thus was any month in which returns from the Russell 3000 Index lost value for a second or greater consecutive month. If the end of month value had gone down for two or more months, then this indicated negative market growth, reflecting the timing within which market irregularities in the form of investor behavior are noticed (García, 2013). Comparing the data generated a binary independent variable, with a value of one for any given month in which the Russell 3000 Index had a smaller return than the preceding two months. The variable had a value of zero for months that did not meet that criterion.

Like the independent variable, the dependent variables also required definition prior to its calculation. Estimated prediction error was the overarching variable that represented the accuracy of asset pricing models. The use of this measurement error in a time-series analysis reflected investor risk and the difference between what the models generated and market results (Greenwood and Shleifer, 2014). Estimated prediction error levels that fell outside of a statistically significant range indicated a difference between predicted and actual behavior in investments (Brown and Walter, 2013). As specified in the research questions, there were three measurements for estimated prediction error: Jensen's alpha, Sharpe's ratio, and the Treynor measure.

The use of three separate measurements to quantify a single construct served two purposes. First, it established validity and allowed better conclusions if the results for each variable demonstrated a similar result (Betker and Sheehan, 2013). Second, the use of multiple variables allowed the research to circumvent the limitations of any single variable. For instance, the Sharpe ratio held the assumption that returns have a normal distribution, while hedge funds, as an example, significantly deviate from normality (Mistry and Shah, 2013). While the Treynor and Jensen' variables did not have the same limitation, the Treynor measure hypothesized that betas, or systematic risk, are stationary, while Jensen's alpha was a relative measure, as opposed to the absolute measures of Sharpe and Treynor (van Dyk, van Vuuren, and Heymans, 2014). Using all of these measures provided a level of sensitivity analysis, aiding robustness and external validity of the research.

Each of the three estimated prediction error methods required specific calculations as dependent variables. Jensen's alpha is the difference between the investment return and the sum of the risk-free rate and systematic risk (Black et al., 1972), or $Ri - [Rf + \beta(Rm - Rf)]$. For this equation, Ri was the realized return of each specific firm for the month, Rm was the realized return of the market, Rf was the risk-free rate of return, and β was the systematic risk of the firm investment. The Sharpe ratio is the ratio between the difference of investment and risk-free return and the standard deviation of the investment (Sharpe, 1994), or $(Ri - Rf) / \sigma i$. The only additional data need for this equation beyond Jensen's alpha is σi, the standard deviation of the investment. Finally, the Treynor measure is similar to the Sharpe ratio but with the divisor as beta rather than the standard deviation (Treynor, 1965), or $(Ri - Rf) / \beta$.

Based on the three estimated prediction error calculations, the required data was the 1994-2016 monthly return for each of the 36 consumer staple and 87 consumer discretionary firms as well as the monthly beta and standard deviation for each of these firms. Additional necessary data were the monthly return of the market proxy, which as previously mentioned was the Russell 3000 Index, and the monthly risk-free rate. Like the market return, the risk-free rate also required a proxy. One-month U.S. Treasury bill rates acted as this proxy since the one-month bill rate reflects an appropriate measure for time comparisons (Smith and Walsh, 2013). The selection of short-term U.S. Treasury Bills as a proxy for risk-free investments is common since they are liquid, considered historically default free, and theoretically available to all investors (Perold, 2004).

There are limitations to the use of U.S. Treasury bills as a proxy. One area of concern is that U.S. Treasury Bills may not actually represent what investors have available to them as investments. An examination of European markets, for example, would not have U.S. Treasury securities as an appropriate proxy (Dichtl and Drobetz, 2011). Generally, any use of an international model needs a more global proxy for the risk-free rate than U.S. Treasury Bills (Perold, 2004). However, in this case, the overall population is strictly part of the U.S. market, and Treasury Bills reflected a solid, constant maturity investment, adjusted for inflation rates (Zaimović, 2013).

Conducting the census consisted of gathering the secondary data required for calculation of the independent and dependent variables. For the independent variable of extended negative market growth, this meant the monthly returns of the Russell 3000 Index from 1994 through 2016, which served as a proxy for the overall market. Calculating consecutive month losses showed that of the 276 months included in the research, 48 were recessionary periods and 226 were growth. The total number of data points for each period depended on the initial data points of individual equities.

Regarding the six dependent variables of estimated prediction error, the calculations required the market proxy, the monthly return on one-month Treasury bills that served as proxy for the risk-free rate, as well as the monthly return, beta, and standard deviation for each of the stocks in the staple goods and discretionary goods sectors. The monthly estimated prediction errors of Jensen's alpha, the Sharpe ratio, and the Treynor measure were calculated for each of the 276 months of the research timeframe from the data of the 36 consumer staples and 87 consumer discretionary firms. Since some of the firms did not have public stock at the beginning of the research period, those months for those firms could not be included in the analysis. After eliminating those nonexistent data points, the numbers of total dependent variable points were 8,727 for the staple goods and 19,009 for the discretionary goods. The elimination of missing data also resulted in a breakdown of 7,458 growth points and 1,269 recessionary points for staple goods and 16,233 growth with 2,776 recessionary for discretionary goods. Further examination of the data provided results demonstrating that the assumptions of the t-test were met. The descriptive statistics for the dependent variables are listed in Table 1.

Table 1: Descriptive Statistics of the Dependent Variables

Dependent Variable	*N*	Mean	Standard Deviation
Combined population (staple and discretionary goods)			
Jensen's alpha	27,736	30.42	134.60
Sharpe ratio	27,736	-0.09	0.90
Treynor measure	27,736	-1.18	191.00
Staple goods variables			
Jensen's alpha	8,727	12.84	55.43
Sharpe ratio	8,727	-0.14	0.83
Treynor measure	8,727	-2.63	140.13
Discretionary goods variables			
Jensen's alpha	19,009	38.50	157.54
Sharpe ratio	19,009	-0.07	0.94
Treynor measure	19,009	-0.52	210.27

This table summarizes the descriptive statistics (population size, mean, and standard deviation) of the three dependent variables measuring estimation error for the two research question populations, namely staple vs. discretionary goods, as well as the combined population.

RESULTS AND DISCUSSION

Testing for Difference in Estimated Prediction Errors for Staple Goods Firms

The first of two research questions this study sought to answer pertained to the consumer staples firms as listed in the S&P 500 and asked, "Was there a statistically significant difference between the asset pricing model estimated prediction errors for staple goods firms during recessionary periods and the estimated prediction errors in growth periods?" The null hypothesis stated that there was no significant difference between the estimated prediction errors for stocks in the consumer staples industry during periods of extended negative market growth and for the same stocks during periods not in extended negative market growth. The alternate hypothesis stated that there was a significant difference between the estimated prediction errors for stocks in the consumer staples industry during periods of extended negative market growth and for the same stocks during periods not in extended negative market growth. Since this research included three measures of the estimated prediction error, there were three separate tests regarding the overall hypothesis. Table 2 summarizes the descriptive statistics for the dependent variables pertinent to this first research question as grouped by growth or recessionary period.

Table 2: Descriptive Statistics of Staple Goods Dependent Variables by Period

Dependent Variable	*N*	Mean	Standard Deviation
Growth period			
Jensen's alpha	7,458	10.422	42.699
Sharpe ratio	7,458	-0.096	0.801
Treynor measure	7,458	-1.553	137.072
Recessionary period			
Jensen's alpha	1,269	27.053	100.927
Sharpe ratio	1,269	-0.376	0.933
Treynor measure	1,269	-8.952	156.830

This table summarizes the descriptive statistics for the estimation errors of staple goods firms as separated into periods of growth in the overall market and recession in the overall market.

The first test regarding staple goods firms examined Jensen's alpha for recessionary and growth periods. The null hypothesis was rejected based on the results of the t-test. As indicated in Table 2, on average, the estimated prediction error for recessionary periods was larger than for growth periods when measured using Jensen's alpha. This difference was significant, $t(8725) = -9.935$, $p < 0.001$, with a small to medium effect size, as shown in Table 3. This indicates, based on both confidence interval and statistical significance, that for staple goods during recessionary periods, asset pricing models are less accurate than during growth periods when measured using Jensen's alpha.

The same methodology was applied to examine staple goods firms concerning the Sharpe ratio. Like with Jensen's alpha, the null hypothesis was rejected based on the t-test. On average, the estimated prediction error measured using the Sharpe ratio was larger in a negative direction for recessionary periods than for growth periods. This difference was significant, $t(8725) = 11.229$, $p < .001$, with a small to medium effect size. This indicates, based on both confidence interval and statistical significance, that for staple goods during recessionary periods, asset pricing models are less accurate than during growth periods when measured using the Sharpe ratio.

The final test with the first research question used the t-test to examine the estimated prediction error as measured using the Treynor measure for staple goods firms. Unlike with Jensen's alpha and the Sharpe ratio, the results of the t-test failed to reject the null hypothesis. While, on average, the estimated prediction error for recessionary periods was larger than for growth periods, this difference was not statistically significant, $t(8725) = 1.739$, $p = .082$, with a small effect size. Based on both confidence interval and statistical significance, this indicates that for staple goods during recessionary periods asset pricing models may be no more or less accurate than during growth periods when measured using the Treynor measure.

Table 3: Independent t-test Results for Estimated Prediction Error of Staple Goods Firms

Dependent Variable	*T*	*DF*	2-Tailed Significance	Mean Difference	95% Confidence Interval		Duration
					Lower	Upper	
Jensen's alpha	-9.935	8,725	<0.001	-16.631***	-19.912	-13.349	0.389
Sharpe ratio	11.229	8,725	<0.001	0.280***	0.231	0.329	0.350
Treynor measure	1.739	8,725	0.082	7.400	-0.941	15.740	0.053

*Results of the t-test for the first research question as to whether asset pricing model estimation errors are significantly different for staple goods firms during recessionary versus non-recessionary periods. Note that the results indicate significance with regards to measurement via Jensen's alpha and the Sharpe ratio, but not with the Treynor measure.*** The mean difference is significant at the 1% level.*

Testing for Difference in Estimated Prediction Errors for Discretionary Goods Firms

The second research question repeated the format and procedures of the first but examined the consumer discretionary rather than consumer staples firms of the S&P 500. The importance of this question was to determine if there was a difference in results when looking at a traditionally more volatile sector than the relatively stable staples good sector (Rostan and Rostan, 2012). The null hypothesis for this question stated that there was no significant difference between asset pricing model estimated prediction errors for stocks in the consumer discretionary industry during periods of extended negative market growth and for the same stocks during periods not in extended negative market growth. The alternate hypothesis stated that there was a significant difference between estimated prediction errors for stocks in the discretionary goods industry during periods of extended negative market growth and for the same stocks during periods not in extended negative market growth. As with the first research question 1, there were three measures of estimated prediction error, and Table 4 summarizes the descriptive statistics of the dependent variables for this question, while Table 5 lists the t-test results.

Table 4: Descriptive Statistics of Discretionary Goods Dependent Variables by Period

Dependent Variable	*N*	Mean	Standard Deviation
Growth period			
Jensen's alpha	16,233	31.002	129.338
Sharpe ratio	16,233	0.013	0.904
Treynor measure	16,233	0.276	186.953
Recessionary period			
Jensen's alpha	2,776	83.320	264.409
Sharpe ratio	2,776	-0.560	0.977
Treynor measure	2,776	-5.157	313.679

This table summarizes the descriptive statistics for the CAPM estimation errors of consumer discretionary goods firms as separated into periods of growth in the overall market and recession in the overall market.

As with staple goods firms, the first test regarding discretionary goods firms examined Jensen's alpha for recessionary and growth periods. The null hypothesis was rejected based on the results of the *t*-test. On average, the estimated prediction error for recessionary periods was larger than for growth periods. This difference was significant, $t(19097) = -15.965$, $p < .001$, with a medium effect size, $d = .405$. This indicates, based on both confidence interval and statistical significance, that for discretionary goods during recessionary periods, asset pricing models are less accurate than during growth periods when measured using Jensen's alpha.

When examining estimated prediction error as measured by the Sharpe ratio for discretionary goods firms as measured by the Sharpe ratio, a similar result was obtained. The null hypothesis was rejected based on the results of the *t*-test. On average, the estimated prediction error for recessionary periods was larger than for growth periods, with a significant difference, $t(19097) = 30.458$, $p < .001$, and a medium to large effect size, d = .634. This indicates, based on both confidence interval and statistical significance, that for discretionary goods during recessionary periods, asset pricing models are significantly less accurate than during growth periods when measured using the Sharpe ratio.

As with the first research question 1, when examining estimated prediction error of discretionary goods firms as measured by the Treynor measure for recessionary and growth period, the results of the t-test failed to reject the null hypothesis. On average, the estimated prediction error for recessionary periods was larger than for growth periods, but this this difference was not significant, $t(19097) = 1.258$, $p = .208$, with an extremely small effect size. Based on both confidence interval and statistical significance, this indicates that for discretionary goods during recessionary periods, asset pricing models may be no more or less accurate than during growth periods when measured using the Treynor measure. Therefore, hypothesis testing across the research questions provided mixed results.

Table 5: Independent t-test Results for Estimated Prediction Error of Discretionary Goods Firms

Dependent Variable	*T*	*DF*	2-Tailed Significance	Mean Difference	95% Confidence Interval Lower	Upper	Duration
Jensen's alpha	-15.965	19007	<0.001	-51.318***	-57.618	-45.018	0.405
Sharpe ratio	30.458	19007	<0.001	0.573***	0.536	0.609	0.634
Treynor measure	1.258	19007	0.208	5.433	-3.030	13.898	0.004

Results of the t-test for the second research question as to whether asset pricing model estimation errors are significantly different for discretionary goods firms during recessionary versus non-recessionary periods. Note that the results indicate significance with regards to measurement via Jensen's alpha and the Sharpe ratio, but not with the Treynor measure.
*** The mean difference is significant at the 1% level.

Combined Analysis of Both Research Questions

The hypothesis testing ultimately provided mixed results. For both research questions, staple and discretionary goods firms, the t-test indicated a rejection of the null hypotheses for Jensen's alpha and the Sharpe ratio indicating that that there was significant difference between estimated prediction errors. However, for both staple and discretionary goods firms, the t-test indicated a failure to reject the null hypothesis concerning the Treynor measure. Given these mixed results, one initial area to re-examine is whether the data we analyzed actually met the assumption requirements for the conducted t-test. Although the t-test assumptions did hold, it is important to note that failing to meet these assumptions could affect internal or external validity. These assumptions include normality, linearity, and homoscedasticity (Field, 2013).

The tests conducted for normality appear to indicate that the distributions of the estimated predictor variables were not normal. In all six cases of the dependent variables, the Kolmogorov-Smirnov statistic indicated a lack of normality ($p<0.001$) and the P-P plots for Jensen's alpha and the Treynor measure deviated significantly at the extremes. A significant level of leptokurtosis contained within these variables may explain this deviation, as well as why the Sharpe ratio did not indicate the same deviation. In the case of staple goods, the kurtosis for Jensen's alpha and the Treynor measure was 164.401 and 512.406 respectively while that of the Sharpe ratio was only 2.304. For discretionary goods, these values were 243.891 for Jensen's alpha, 1951.126 for the Treynor measure, and only 11.376 for the Sharpe ratio. Ultimately, however, there are several reasons why this apparent lack of normality may not hinder the overall validity of the t-tests.

First, the deviation from normality that appears in testing is of lesser importance than may be expected due to the underlying population, the census size, and the kurtosis factor (Field, 2013). While it appears that the dependent variables may not have a normal distribution, previous research has established that both of the population sectors, staple and discretionary goods firms, demonstrate normality in their return data (Cheung, 2013). The assumption of the t-test is that the variable within which the t-test value is calculated has a normal distribution. Although error distributions, which are the dependent variables in this research, are not normally distributed, the underlying factors strengthen the robustness of results (Pesaran and Yamagata, 2012). In other words, even if the distribution of the dependent variable is not normal, the statistical results retain validity. The leptokurtic shape of this distribution can also affect internal validity if not explained by underlying factors.

The use of beta in calculating Jensen's alpha and the Treynor measure can explain the presence of kurtosis in those calculations while not in the Sharpe ratio. The calculation of β relies on the covariance of returns, which means there is a timing factor wherein the beta is more volatile with fewer data points (Bartram et al., 2015). Stocks with initial public offerings within the period of the study are likely to have higher individual kurtosis based on abnormal initial positive returns followed by three to five years of abnormal negative returns (Conrad, Dittmar, and Ghysels, 2013). Since this research added these equities upon their market entry, it is likely to demonstrate this increased kurtosis when the beta is calculated, which is not a factor for the Sharpe ratio. Of greater importance than the reason for the presence of kurtosis is the impact that kurtosis has the eventual analysis of results. It is important to note that even though kurtosis exists, skewness does not. With large sample sizes, the lack of skewness, or equal distribution on either side of the median, is of greater importance to test validity and robustness than the presence of kurtosis (Conrad et al., 2013). In this way, the quantity of data minimizes the impact of kurtosis, as well as the potential of normality as a whole.

In addition, the size of the census, with 8,727 data points for each dependent variable in the staples sector and 19,009 in the discretionary sector, invokes the central limit theorem. According to this theorem, any sufficiently large sample, or in this case census, demonstrates a normal distribution, and statistical tests that require normality can be applied (Field, 2013). The sample size required for this theorem to apply is generally thought to be 30 (Mertler and Vannatta, 2013), so this study greatly exceeds that threshold. Additionally, while the Kolmogorov-Smirnoff test indicates a lack of normality, this test can indicate significance for irrelevant effects if the sample size is large. Again, the size of the census dictates an acceptance of normality or, at the very least, acceptance of results even if the distribution is less than normal.

Moreover, plotting the residual errors against the predicted errors for each of the dependent variables provided results that argued in favor of accepting the linearity and homoscedasticity assumptions. This lack of assumption violation indicated no systematic relationship in the errors that could convolute the eventual results of the t-test. The zpred vs. zresid scatterplots demonstrated neither a curvilinear shape nor funneling, indicating acceptance of the linearity and homoscedasticity assumptions for each dependent variable (Field, 2013). While conducting Levene's test could have provided further examination of potential heteroscedasticity, Levene's test, like the Kolmogorov-Smirnov test, is subject to false positive results with large sample sizes and is less accurate with unequally sized groups (Mertler and Vannatta, 2013), as was the case with this study. The large sample size and corresponding large degrees of freedom for hypothesis testing minimize the risk of invalidity even with a slight violation of the linearity and homoscedasticity assumptions.

Furthermore, users of asset pricing models expect some degree of error due to the uncertainty inherent in making ex-ante decisions (Greenwood and Shleifer, 2014). However, an increasing level of error when associated with a changing factor, as demonstrated with two of the three measures, lends credence to the premise proposed in behavioral finance theory that some level of error is environmentally attributable as opposed to a mathematical issue (Brown and Walter, 2013). In other words, if one assumes that betas were not stable, thereby rendering the Treynor measure as less accurate (van Dyk et al., 2014), then this study does lend weight to the argument that investor behavior is unpredictable at times. Additionally, the smaller error measurements during market growth periods indicate the model's theoretical underpinnings are also correct, namely that the model is accurate when investors are rational.

One major conflict between advocates of behavioral finance theory and critics who espouse a more traditional examination of the market using asset pricing models is the impact of the individual investor versus a market that averages out irrational outliers. Theory proponents posit that irrational investor behavior disrupts the market to a significant level (Mitroi and Oproiu, 2014). The results of four of the six sub-questions add weight to this argument. When measured by Jensen's alpha or the Sharpe ratio, the difference between estimated prediction errors is significantly greater during recessionary irrational periods with generally medium effect. Proponents of asset pricing models counter that, per the efficient market hypothesis, the market averages out irrational investors, thus the model remains a valid instrument (Smith and Walsh, 2013). The results of testing with the Treynor measure support that argument, with a failure to reject the null hypotheses and a very small effect size. Since this study did not provide definitive support to either argument regarding the overall acceptance of behavioral finance theory, it is appropriate to consider what differences existed in the estimated prediction errors to cause the differing results.

To discover possible differences, a possible starting point in examining correlation. The correlation among the variables was consistent, as seen in Table 6. Whether looking at the entire population or either of the sectors, staple goods or discretionary goods, there is little indication of correlation between the Treynor measure and either Jensen's alpha or the Sharpe ratio. This is true for both recessionary and non-recessionary periods, with the absolute value of the correlation coefficient never rising above 0.065. However, the correlation between Jensen's alpha and the Sharpe ratio indicates a medium effect. There is a positive correlation between the two variables during non-recessionary periods, 0.321 for the entire population, and a negative correlation during recessionary periods, -0.484. Again, this is the case for either sector alone as well as for the entire population as a whole.

Table 6: Correlation Coefficients among the Calculated Estimated Prediction Errors

Dependent Variable Comparison	Entire Population		Staple Goods Sector		Discretionary Goods Sector	
	Non-Recessionary Periods	Recessionary Periods	Non-Recessionary Periods	Recessionary Periods	Non-Recessionary Periods	Recessionary Periods
Jensen's alpha – Sharpe ratio	0.321	-0.484	0.355	-0.341	0.333	-0.532
Jensen's alpha – Treynor measure	0.015	-0.019	0.017	-0.022	0.015	-0.020
Sharpe ratio – Treynor measure	0.050	-0.001	0.063	0.013	0.046	-0.003

Results of calculating the correlation coefficient between each of the dependent variable pairings. The results indicate little correlation between the Treynor measure and either of the other two variables, but medium correlation between Jensen's alpha and the Sharpe ratio.

All three calculations of estimated prediction error, i.e., Jensen's alpha, the Sharpe ratio, and the Treynor measure, stem from the same underlying data regarding individual equity returns and the risk-free rate (Kan, Robotti, and Shanken, 2013). The differences lie in how they use that data to calculate estimated prediction error. While Jensen's alpha uses beta as a factor to add to the error measure, the Treynor measure divides by beta and the Sharpe ratio does not use beta at all. Therefore, large betas would generally result in Jensen's alpha being more negative, have no impact on the Sharpe ratio, and cause the Treynor measure to cluster closer to zero. A more accurate asset pricing model would have an estimated error that approached zero (Black et al., 1972, Dempsey, 2013). Larger betas are indicative of a volatile market (Rostan and Rostan, 2012), and Treynor (1965) assumed stationary betas with his measure, since repeatedly confirmed (Mahakud and Dash, 2016).

This difference in the influence of beta on the Treynor measure both explains the discrepancy in results and affects the interpretation of these results. If the market is less stable and more volatile during market downturns, as proposed by Hillson et al. (2014), then the betas during these periods will cause a more clustered Treynor measure, rendering that result less useful. This would add weight to the results as demonstrated by Jensen's alpha and the Sharpe ratio and the interpretation that irrationality does negatively influence the accuracy of the asset pricing model. On the other hand, if the market retains overall stability even while trending downward, as theorized by Pesaran and Yamagata (2012), then the results as demonstrated by the Treynor measure have greater weight, countering the irrationality argument.

Comparing the results of the two separate research questions, for staple goods versus for discretionary goods, lends evidence to an interpretation of this discrepancy. Discretionary goods firms tend to have higher volatility across the market over the long run than staple goods firms (Rostan and Rostan, 2012). Thus, if the market were generally stable overall, then the consumer discretionary sector should have somewhat higher volatility over that of the consumer staples sector, even while remaining statistically insignificant. Instead, results or our study indicated that the effect size was greater in discretionary goods for Jensen's alpha and the Sharpe ratio, but significantly smaller for the Treynor measure. This opposite result, while by no means definitive, does add additional credence to the argument that the market was more unstable and thus irrational behavior both existed and affected the accuracy of asset pricing.

With an understanding that, given a particular set of circumstances, investors, or groups of investors may not operate in a predictable manner, then applying behavioral finance theory means examining what specifically is causing this unpredictability. The psychological factors demonstrated in some of the outcomes potentially creating the discrepancy were beyond the scope of this study. These could include overconfidence, self-deception, or cognitive dissonance (Shankar and Dhankar, 2015). The results do indicate that there appears to be a change in behavior from what is expected during a down market, based on the effect size and statistical significance of the hypotheses testing, even if this change is not irrationality. Thus, even had the study not concluded with mixed results, it would indicate the plausibility that, in accordance with behavioral finance theory, investor behavior interferes with long-term goal planning while also demonstrating the limitations of behavioral finance theory, which is the difficulty in attributing a level of unpredictability (Baker and Ricciardi, 2015).

While a causal-comparative analysis cannot definitively prove direct causation, and thus one cannot in this case outright accept or reject behavioral finance theory, such a study can provide strong evidence for that linkage. In the case of this research, the previous literature implied that psychological or sociological factors could cause discrepancies in traditional models that are not merely aggregated across the market (Thaler, 2015). At times, investor behavior is irrational and that irrationality violates the assumptions of asset pricing models. Therefore, irrationality should cause these models to be less accurate. Since irrationality occurs during recessionary periods, during those periods the models should have had greater error. However, the mixed results of this research provided conflicting evidence at best for the causality that behavioral finance theory predicts.

Thus, the study findings imply that analysts or investors need to exercise extra caution with asset pricing model use. However, the study does not clarify specifically what behavior causes this necessity. During a recessionary period, the model potentially increases prediction error, and an analyst or investor may want to take note of that. However, knowing why the error exists can also assist the analyst or investor in determining precisely how to counter the error. Irrationality, as theorized and demonstrated by García (2013), appears to be a likely factor. However, the study also lends credence to the possibility of the disposition effect, where during a down market, the potential for loss affects investors in an emotional way, thus altering their behaviors and making them less predictable than during an up market (Ye, 2014). This can show up as a change in standard deviation regarding above mean deviations compared to deviations below the mean, as would be the case when the entire market, as opposed to a single equity, is in a downward cycle.

Another potential aspect of behavioral finance theory that can explain behavior change is loss aversion (Guerrero, Stone, and Sundali, 2012). However, reactive loss aversion is not necessarily irrational behavior, depending on a number of factors to include time constraints with personal investor choice (Thaler, 2015). Thus, while this study does appear to present at least some measure of support for behavioral finance theory, it does not address the applicability of the various investor phenomena contained within the overarching theory.

While the study results did not prove to be definitive, it does suggest that analysts and investors exercise some degree of caution when utilizing asset pricing models. Even with mixed results, the rejection of the null hypotheses in four of the six cases, particularly with the effect sizes noted, indicate that as investor behavior deviates from normal, the models become less accurate as predictors. In other words, during a stable but growing market, recommendations made using these models may come accompanied with a strong probability of accuracy. However, if the market is both more volatile and trending downwards, thus having a greater likelihood of irrationality affecting not only the market but also individual investments, then recommendations provided using the model might also contain a greater degree of caution regarding implementation.

The impact that beta appears to have on the study results also has implications for users of asset pricing models. When beta values are larger, the estimated prediction error will be larger for Jensen's alpha but smaller for the Treynor measure. A volatile beta means that there will be greater instability in the model and greater discrepancies between interpretations of the estimated prediction errors. Therefore, environmental conditions that result in a widely varying beta value provide less reliability and validity for the model as a prediction or analysis tool. These conditions include economic factors, such as timing since initial public offering (Bilinski and Lyssimachou, 2014), and behavioral factors like reactions to positive outlooks as opposed to risk adversity (Kahn and Lemmon, 2016).

Additionally, this study points to the importance of investor knowledge of what causes anomalies in asset pricing models and the impact of environmental factors on irrationality. The presence of irrational behavior and the uncertainty that this brings to the market, both in terms of predictability and actual results, means both the potential for greater investor opportunity and a need for more human interpretation of model results (Hillson et al., 2014). Thus, an investor or advisor who wishes to incorporate behavioral finance into their overall investment strategy must have a greater understanding of human psychology than traditional model interpretation would impose.

CONCLUDING COMMENTS

As outlined in the literature review and presented again through this study, the discrepancy between the utility of asset pricing models and the problems inherent in their assumptions was apparent. This study directly reflected this discrepancy as behavioral finance theory provided a challenge to the assumption of the rational investor upon which asset pricing builds (Mankert and Seiler, 2012). Behavioral finance offers numerous theoretical and empirical examples of investors behaving in an irrational manner, particularly when the market is falling (García, 2013). Proponents of asset pricing models counter that even with irrational investors, the models are still empirically valid and practically useful (Smith and Walsh, 2013). This research hoped to provide some empirical evidence supporting one side or the other of this debate.

In summary, this study was a quantitative, nonexperimental, causal-comparative secondary data analysis. Using historical data allowed the calculation of the estimated prediction errors for asset pricing models in accordance with the widely accepted methodology established by Black, Jensen, and Scholes (1972). Their foundational methodology entails calculating a prediction error by calculating a time series comparison of the model's predicted value with actual values. There are various methodologies for determining the prediction error deviation, dependent upon the significance of volatility and normalcy in the population (Mistry and Shah, 2013). Therefore, this study included the calculations of the Sharpe ratio, Jensen's alpha, and the Treynor measure, all based on the seminal works of their authors, and tested over time (Brown and Walter, 2013).

Does investor irrationality as demonstrated during recessionary periods alter the estimated prediction error of asset pricing models? For both the staple and discretionary good sectors, there is evidence to support answering this positively, at least as measured by Jensen's alpha and the Sharpe ratio. Both measures indicated an average medium effect size at a statistically significant level. However, the same is not true when looking at the Treynor measure as the estimated prediction error, as the evidence, in this case, points to a lack of causality, although there may be confounding factors such as the volatility of beta within the data (Bilinski and Lyssimachou, 2014). Thus, while the results of this research and the implications of these results may be mixed, the study added to the overall body of knowledge by providing both a certain level of empirical validity as well as guidance toward future research in the crossroads between behavioral finance and asset pricing models.

One major limitation of this study was inherent in the nature of the research design. A causal-comparative approach only suggests causation and cannot prove that linkage. Even definitive rejection of the null hypothesis for every sub-question would not unequivocally demonstrate a linkage between irrationality and model error. Thus, an understanding of the limitations of non-experimental research must temper any conclusions from this study. Additionally, the mixed results, even considering the impact of a volatile beta, prevent a wider acceptance of the conclusions.

Additional study limitations include issues with the selected population and data utilized. The population selected, namely that of the consumer staples and consumer discretionary sectors, represented two segments of the overall market with anticipated discrepancies in volatility and return. Using these two sectors allowed for sufficient data and comparability without creating a situation wherein the data set became unreasonable to manage within the time constraints of the research. The inclusion of additional market sectors, up to and including the entire market, would have provided a more thorough analysis of the research problem, and thus increased external validity. Likewise, the research included only data from 1994 through 2016. Expanding the data to include earlier dates would have provided increased reliability by increasing the overall size of the census. However, this was not feasible, as the data for the market proxy, the Russell 3000 Index, did not exist prior to 1994. A lack of available data also affected certain segments of the population that were not included.

Historical stock market data sites had readily available information concerning those equities that were still actively traded. However, data was not readily available for equities that stopped trading prior to December 2016. Delisted company information is both difficult and costly to obtain, and does not guarantee inclusion of standard deviation or beta as required for estimated prediction error calculation. This means that the analysis contained in this research is subject to the potential for survivor bias, meaning that unsuccessful businesses with low returns are not included, potentially skewing results (van Dyk et al., 2014). The previously mentioned date cutoff offsets this limitation, since increasing the timeline of the research population would either have increased the impact of survivor bias or required a potentially unmanageable set of data within the constraints of time and budget. These limitations notwithstanding, there are implications for both financial practitioners and scholars.

Both the mixed results regarding hypothesis testing and the limitations of the study provide guidance for potential future research. Expanding the research population could generate greater clarification and sensitivity analysis. Methods to increase the population include expanding the timeline of the study, testing additional or alternative market sectors, up to and including the entire market, or incorporating delisted equities. Expanding the population in this way could both increase external validity, potentially alter the conflicting hypotheses results, and reduce the previously mentioned survivorship bias.

Related to changing data within the market, another recommendation is completely changing the market for the study. The examination of a different market could have implications for external validity. For example, the European stock market tends to be less volatile in equivalent sectors as a whole than the U.S.

stock market (Bartram et al., 2012). Since the results of this study, particularly concerning the Treynor measure, suggest that volatility affected the results of hypothesis testing, examining a market with less volatility to compare results can provide insight into overall applicability.

Other possible future research entails modifying the research design in data selection. Asset pricing models, specifically regarding beta, is sensitive to the time period used in its computation (Kahn and Lemmon, 2016). Therefore, replicating this research using returns on a timeline that differed from the monthly data this study used could result in a very different outcome. The applicability of those results, as compared to current results, would depend on the manner in which the analyst or investor planned to use an asset pricing model and the inputs to that model. Related to timelines and the impact of beta is the sensitivity of beta to initial data due to its calculation as a correlated variable (Conrad et al., 2013). Choosing to exclude equities in their first year after initial public offering, for example, would preclude some of the more aberrant beta calculations. This, in turn, would reduce the existence of outliers, decrease the standard deviation, and potentially alter the outcome of hypothesis testing. This could then lend credibility to a specific timing factor of accepting or rejecting the use of an asset pricing model based on irrational behaviors for equities in their initial periods of trading.

A final method of altering research design to provide additional insight towards the research problem would be to select alternative proxies for either the overall market or the risk-free rate. The research design as conducted included proxies that best replicated the market given the specified population. Since the census examined monthly returns, for example, then the one-month U.S. Treasury bill represented the most accurate representation of risk-free rate (Smith and Walsh, 2013). Likewise, the Russell 3000 Index as the overall market proxy reflected the U.S. equity market within which the population of consumer staples and consumer discretionary equities resided. A replication of results from this study with the use of a different proxy may lend validity to the conclusions being the result of actual causality of irrationality rather than the result of inaccurate proxy selection (Brown and Walter, 2013). While conducting a replication or alternative to this study using any of the methods outlined above would necessarily have costs in terms of both time and money, the additional insight provided would strengthen the overall conclusions and applicability.

APPENDIX

Appendix A: List of Firms in the Research Population

Firms in the Consumer Staple Goods Sector	
Altria Group Inc (MO:NYQ)	Archer Daniels Midland Co (ADM:NYQ)
Brown-Forman Corp (BF.B:NYQ)	Campbell Soup Co (CPB:NYQ)
Church & Dwight Co Inc (CHD:NYQ)	Clorox Co (CLX:NYQ)
Coca-Cola Co (KO:NYQ)	Colgate-Palmolive Co (CL:NYQ)
Constellation Brands Inc (STZ:NYQ)	Costco Wholesale Corp (COST:NSQ)
Coty Inc (COTY:NYQ)	CVS Health Corp (CVS:NYQ)
Dr Pepper Snapple Group Inc (DPS:NYQ)	Estee Lauder Companies Inc (EL:NYQ)
General Mills Inc (GIS:NYQ)	Hershey Co (HSY:NYQ)
Hormel Foods Corp (HLR:NYQ)	J M Smucker Co (SJM:NYQ)
Kellogg Co (K:NYQ)	Kimberly-Clark Corp (KMB:NYQ)
Kraft Heinz Co (KHC:NYQ)	Kroger Co (KR:NYQ)
McCormick & Company Inc (MKC:NYQ)	Mead Johnson Nutrition Co (MJN:NYQ)
Molson Coors Brewing Co (TAP:NYQ)	Mondelez International Inc (MDLZ:NYQ)
Monster Beverage Corp (MNST:NSQ)	PepsiCo Inc (PEP:NYQ)
Philip Morris International Inc (PM:NYQ)	Procter & Gamble Co (PG:NYQ)
Reynolds American Inc (RAI:NYQ)	Sysco Corp (SYY:NYQ)
Tyson Foods Inc (TSN:NYQ)	Wal Mart Stores Inc (WMT:NYQ)
Walgreens Boots Alliance Inc (WBA:NSQ)	Whole Foods Market Inc (WFM:NSQ)

Firms in the Consumer Discretionary Goods Sector	
Advance Auto Parts Inc (AAP:NYQ)	Amazon.com Inc (AMZN:NSQ)
AutoNation Inc (AN:NYQ)	Autozone Inc (AZO:NYQ
Bed Bath & Beyond Inc (BBBY:NSQ)	Best Buy Co Inc (BBY:NYQ)
BorgWarner Inc (BWA:NYQ)	Carmax Inc (KMX:NYQ)
Carnival Corp (CCL:NYQ)	CBS Corp (CBS:NYQ)
Charter Communications Inc (CHTR:NSQ)	Chipotle Mexican Grill Inc (CMG:NYQ)
Coach Inc (COH:NYQ)	Comcast Corp (CMCSA:NSQ)
D. R. Horton Inc (DHI:NYQ)	Darden Restaurants Inc (DRI:NYQ)
Delphi Automotive (DLPH:NYQ)	Discovery Communications Inc (DISCA:NSQ)
Discovery Communications Inc (DISCK:NSQ)	DISH Network Corp A (DISH
Dollar General Corp (DG:NYQ)	Dollar Tree Inc (DLTR:NSQ)
Expedia Inc (EXPE:NSQ)	Foot Locker Inc (FL:NYQ)
Ford Motor Co (F:NYQ)	Gap Inc (GPS:NYQ)
Garmin Ltd (GRMN:NSQ)	General Motors Co (GM:NYQ)
Genuine Parts Co (GPC:NYQ)	Goodyear Tire & Rubber Co (GT:NSQ)
H & R Block Inc (HRB:NYQ)	Hanes Brands Inc (HBI:NYQ)
Harley-Davidson Inc (HOG:NYQ)	Hasbro Inc (HAS:NSQ)
Home Depot Inc (HD:NYQ)	Interpublic Group of Companies (IPG:NYQ)
Kohls Corp (KSS:NYQ)	L Brands Inc (LB:NYQ)
Leggett & Platt Inc (LEG:NYQ)	Lennar Corp (LEN:NYQ)
LKQ Corp (LKQ):NSQ)	Lowe's Companies Inc (LOW:NYQ)
Macy's Inc (M:NYQ)	Marriott International Inc (MAR:NSQ)
Mattel Inc (MAT:NSQ)	McDonald's Corp (MCD:NYQ)
Michael Kors Holdings Ltd (KORS:NYQ)	Mohawk Industries Inc (MHK:NYQ)
Netflix Inc (NFLX:NSQ)	Newell Brands Inc (NWL:NYQ)
News Corp A (NWSA:NSQ)	News Corp B (NWS:NSQ)
Nike Inc (NKE:NYQ)	Nordstrom Inc (JWN:NYQ)
Omnicom Group Inc (OMC:NYQ)	O'Reilly Automotive Inc (ORLY:NSQ)
Priceline Group Inc (PCLN:NSQ)	PulteGroup Inc (PHM:NYQ)
PVH Corp (PVH:NYQ)	Ralph Lauren Corp (RL:NYQ)
Ross Stores Inc (ROST:NSQ)	Royal Caribbean Cruises Ltd (RCL:NYQ)
Scripps Networks Interactive Inc (SNI:NSQ)	Signet Jewelers Ltd (SIG:NYQ)
Staples Inc (SPLS:NSQ)	Starbucks Corp (SBUX:NSQ)
Target Corp (TGT:NYQ)	Tegna Inc (TGNA:NYQ)
Tiffany & Co (TIF:NYQ)	Time Warner Inc (TWX:NYQ)
TJX Companies Inc (TJX:NYQ)	Tractor Supply Co (TSCO:NSQ)
TripAdvisor Inc (TRIP:NSQ)	Twenty-First Century Fox Inc (FOX:NSQ)
Twenty-First Century Fox Inc A (FOXA	Ulta Salon Cosmetics Inc (ULTA:NSQ)
Under Armour Inc (UAA:NYQ)	Under Armour Inc (UA:NYQ)
Urban Outfitters Inc (URBN:NSQ)	VF Corp (VFC:NYQ)
Viacom Inc (VIAB:NSQ)	Walt Disney Co (DIS:NYQ)
Whirlpool Corp (WHR:NYQ)	Wyndham Worldwide Corp (WYN:NYQ)
Wynn Resorts Ltd (WYNN:NSQ)	Yum! Brands Inc (YUM:NYQ)

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