

HOW SHOULD BETA INFLUENCE  
INVESTMENT DECISIONS?

By

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### Abstract

In the highly competitive field of finance, investors are constantly trying to invest in stocks and other assets to outperform their peers and various benchmarks. At the center of modern portfolio theory is beta, a necessary component to calculate a stock's expected return and the subject of debate within academia. This paper strives to demonstrate that beta is somewhat when making investment decisions and that while investors should look elsewhere for more relevant factors to make investment decisions, beta can be useful in estimating a stock's risk. This paper will also analyze both the practitioner and academic uses of beta and how theoretical uses of beta have evolved over time as well as calculate beta's predictive ability.

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## Introduction

Long before Dr. Harry Markowitz published the first article on modern portfolio theory, investors have tried to discover, utilize, and implement various investment theories and strategies to gain an advantage over their peers (Keller, 2014). One of the oldest investment opportunities was “tulip bulb mania” centuries ago where speculators drove up the price of tulip bulbs until the market for the prenatal flowers became overbought and collapsed beneath its own weight (Adrego Pinto, 2014). Hundreds of years later, investors and speculators alike still face the effects of severe economic disruption with major interruptions (oftentimes referred to as “recessions”, “financial crises”, or “bubbles”) occurring every five to ten years. However, over the past forty years, one investor managed to outperform his peers and the overall market during that time, Warren Buffet. Warren Buffett’s strategy is to sell stocks for more than he pays while utilizing some amount of leverage to make the purchase (Estrada, 2013). Historically, beta measures the risk of stocks by comparing a security’s return to that of the market and this paper will demonstrate that Buffett’s strategy can be replicated and that, based on the analysis below, beta should not influence investment decisions in estimating returns, but may be helpful in estimating risk.

While much research exists on what beta actually represents and how beta should be measured, by way of academic articles not much exists on how beta *should influence* investment decisions. Currently, beta is viewed as a measure of risk, with the beta of the market (typically the S&P 500 or some other index more comparable to the asset being measured) equaling one (the one exception is

academia is Fisher Black who found that over time, low beta stocks perform better than their high beta peers) (1993). Therefore, stocks with a beta greater than one are viewed as more “risky” relative to the market and stocks with a beta lower than one are less “risky” relative to the market. However, many other factors including, but not limited to, a company’s cash flows, markets in which the company operates, and credit rating also contribute to a company’s risk profile. An analysis by Frazzini & Pedersen demonstrated that low beta stocks have generated returns better than not only the overall market, but also outperformed the returns of high beta stocks, which have underperformed the overall market (2013). After an analysis of Buffett’s investment strategy, the “Oracle’s” strategy implies that by utilizing leverage to purchase low beta stocks, an investor can match the general risk profile of high beta stocks, but have less firm-specific risk in the low beta stocks than in the high beta stocks.

Additionally, low beta stocks are usually indicative of fundamentally strong companies that generate strong cash flow and operate in markets that are less sensitive to economic changes both in good times and bad (the obvious exception are companies that are counter-cyclical and have a low beta due to the nature of the industry [e.g. chemicals and oil]). Therefore, theoretically, beta can be viewed as a single measure of overall “value” or “quality” whose score can be used to differentiate strong companies from others. “Alpha” is a stock’s excess return over the capital asset pricing model (CAPM) and is the main way to compare an investor’s success relative to the market. For example, an investor that buys a stock that returns 25% over the course of a year will generate “alpha” of 5% if the

CAPM states the return should be 20%. CAPM's calculation is unimportant to the discussion of beta and the reader should note that there are many ways to compare stock performance, with alpha being one such way. Because many factors are thought to influence investment decisions (e.g. price-to-earnings ratio, price-to-book ratio, debt-to-equity ratio, etc.), a common starting point is necessary to begin any initial screen and the overall investment process will be objectively verifiable so long as the investment process can be replicated.

Up to this point, research has not dealt with a "basket" of common stocks. Rather, research has evaluated differing securities over differing time intervals and evaluated beta as the key value indicator. This paper will evaluate a total of thirty stocks over differing time intervals with the S&P 500 index performance serving as the study's benchmark and separate the basket of stocks into three portfolios: high beta, middle beta, and low beta. In terms of predicting returns, beta should not influence investment decisions (although beta may be helpful in evaluating risk) and while Buffett's investments have followed the low beta theory, an equally important part of this investment theory is using the correct amount of leverage and not using unnecessarily high levels in order to "juice" returns.

#### Buffett's Strategy Defined

As mentioned in the introduction, Buffett's investment strategy has not been the subject of academic scrutiny for many years with the only two exceptions of Jensen (1984) and Frazzini, Kabiller, and Pederson (2013). In 1984, the authors stated that as great as Buffett's returns had been over the past several decades, his performance should come as no surprise because there will *always* be some

investors that outperform the overall market over a sustained period of time. Buffett's rebuttal was while Jensen's claim was theoretically true, the theory did not apply in Buffett's situation because many investors who held similar strategies have also performed well. Buffett, therefore, claimed that Jensen's theory does not apply because of the statistical improbability that different investors using the same or similar strategies *all* outperformed the overall market. Buffett referred to the investors using a similar investment strategy as living in "Graham-and-Doddsville" (Hanson & Fraser, 2013).

Frazzini, Kabiller, and Pederson (2013) first quantify Buffett's success through evaluating the Oracle's return over the past 30 years and comparing those data to the overall market's return from 1926 – 2011. According to the authors, Buffett's company, Berkshire Hathaway, has the highest Sharpe ratio of any company during the aforementioned time period as well as a "higher Sharpe ratio than all U.S. mutual funds that have been around for more than 30 years" (Frazzini, Kabiller, & Pedersen 2013). Chen, He & Zhang (2011) of the Chinese University of Hong Kong state:

[T]he Sharpe ratio is a measure of efficiency, in terms of the reward, given the level of risks being taken. In this sense, an asset with higher Sharpe ratio is naturally more attractive since it is perceived as making more efficient use of the risks being taken (p.2).

Not only do Buffett and Berkshire Hathaway generate stronger returns than all other peers, they do so with a far lower risk profile which, until recently, was thought to be impossible. While the Sharpe ratio does provide an investor with a company's risk-adjusted return, one of the major assumptions in the calculations is that uncertainty is identical to risk. As Chen, He, and Zhang (2011) point out, the



correlation between uncertainty and risk is “debatable” because “any uncertain gain above the expectation is usually not considered a risk in the ordinary sense (p.2).” In finance, countless definitions of risk exist, but for this writing, risk is defined as the chance or probability of permanent loss of capital.

While low beta, low volatility stocks outperform higher risk peers, outperformance is not so great such that Buffett improves returns solely through stock picking abilities, the other component (as mentioned earlier) is using leverage to magnify the returns of these “cheap” stocks (Black, 1993). Before explaining the specifics of leverage and Buffett’s access to leverage, the reader must be able to distinguish between “cheap” stocks and “rich” or expensive stocks. As Drexel Professors Gray and Vogel point out, stocks that are trading low based on price-to-earnings, free-cash-flow to total enterprise value, and book-to-market ratios are considered to be “cheap” while stocks trading with higher multiples are considered to be “rich” (2011). Determining whether or not a stock is cheap or rich depends on a comparison of the company and its peers within the same industry and not necessarily a company compared to the overall market. For example, companies in the technology sector have higher multiples (on average) compared to companies in the financial services sector and buying a stock in the financial services sector because it is cheap relative to technology would be an invalid conclusion (Guo, et al, 2011). Taking this approach one step further, an investor can evaluate how cheap or rich a sector is compared to the overall market thus adding another point of reference before making an investment decision. For example, if a traditionally low multiple sector such as industrials is trading at a

higher price-to-earnings ratio compared to the S&P 500, a cheap stock in the industrials sector may not necessarily be as cheap as an investor originally thinks. The underlying assumption is that low multiple stocks outperform their peers in the long run and that eventually every company's price-to-earnings ratio eventually trades between roughly 15x and 18x. This range is certainly subject to short-term swings in the market and is more of a "rule of thumb" than canon law.

As for Buffett's specific strategy, he takes the concept of buying low risk, cheap stocks one step further and includes his version of "high-quality" stocks, meaning, "stocks that are profitable, stable, growing, and with high payout ratios" (Frazzini, Kabiller & Pedersen, 2013). Each component of Buffett's stock quality criteria can be differently interpreted by investors because each criteria (besides high payout ratios) can be calculated in many ways depending on a company's stage in its life cycle and the industry in which it operates. For example, a mature company within the healthcare sector is likely to use net income as a measure of profitability because healthcare is a standardized industry and mature companies are unlikely to have the same risk profile as younger, more growth oriented companies.

Simply put, an investor cannot evaluate a company's earnings if the company has no or negligible earnings in which case the investor would look to other measures of profitability such as earnings before interest and taxes (EBIT) or earnings before interest, taxes, depreciation and amortization (EBITDA). However, in the case of Buffett, he looks to invest in companies that are profitable based on both net income and either EBIT or EBITDA. The determination to use

either EBIT or EBITDA is based on whether or not the company has significant capital expenditures (capex) because as Buffett once quipped, “(d)oes management think the tooth fairy pays for capital expenditures (Gardiner, 2009)?” An investor should use EBIT when capex is a significant expense for the company and common throughout an industry and should use EBITDA when capex is insignificant when capex is not commonplace within an industry. For example, a manufacturing company or a railroad company would use EBIT because the cost of building new facilities or replacing old train tracks is a significant expense common throughout each industry. A start-up technology firm would use EBITDA because it is unlikely to have significant expenses and even if it does, capex is not commonplace for high-technology firms.

The next two criteria, stable and growing, are more subjective than profitability because an investor can pick stocks based on different types of profit, but there are only a handful of commonplace profitability measurement. Company stability is difficult to define (even in Buffett’s strategy) because investors determine stability on a case by case basis and while there is no set definition, stable companies generally exhibit the following characteristics: consistent management team, revenue and earnings in the same general range or trend over a significant period of time, either minimal legal issues or well anticipated legal issues, and a well-defined product offering. The cornerstone of stability is a company’s management team because management makes all of the major decisions that influence a firm’s short-term needs and long-term goals. Revenue and earnings stability refers to companies growing at predictable rates (see below).

In some industries such as healthcare equipment manufacturers or tobacco companies, lawsuits are commonplace and expected. Therefore, so long as a firm in this industry has fairly consistent legal expenses, an investor can make an informed decision on future legal expenses. Lastly, a well-defined product offering refers to a company that investors know what a company does and understands how the company and industry will innovate as well as understand the company's competitive advantage(s).

Similar to measuring stability, growth (and really growth drivers) is determined on a case-by-case basis whereby an investor evaluates the company's growth on a standalone basis, the industry's growth prospects, and potentially the overall economy's growth. Historically, two macroeconomic drivers have been evaluated when judging the overall economy: GDP growth and population growth (Cornell, 2010). While these growth drivers are imperative to evaluating the current state of the economy and future growth prospects, strong growth numbers do not necessarily equate to strong earnings growth and ultimately, equity investments are based on earnings growth (Cornell, 2010). Additionally, industry-specific growth drivers can be deduced from compiling historical data and measuring the correlation between that data and earnings. For example, in times of strong economic growth, companies within the consumer discretionary sector are likely to outperform other industries due to the growth expected from a rising economy. Lastly, high payout ratios are generally viewed as stocks that pay out 35% or more in dividends to shareholders.

### What is Beta?

In its simplest form, beta is the regression of a stock's total return compared to that of the market (Frazzini & Pedersen, 2013). However, academicians and practitioners alike have different ways of estimating total return (e.g. using daily returns, weekly returns, monthly returns, etc.) as well as determining which benchmark fits the company best. As mentioned earlier, a beta of one represents a stock that has equal risk relative to the broader market, a lower beta stock theoretically has less risk than the overall market and has a beta of less than one, and a stock with greater risk than the market has a beta of greater than one. Additionally, as mentioned above, recent research has shown that that low beta stocks actually outperform the market as supported by Clarke, Silva & Thorley (2010). The overall goal of their study was to “derive an analytic solution for the long-only minimum variance portfolio under the assumption of a single-factor covariance matrix” or in simpler terms, develop a method by which an investor can evaluate a single factor and achieve the highest risk-adjusted return (Clarke, Silva & Thorley, 2010, p.2). Since the authors confirmed that which was already widely accepted and “proven”, this writing will not break down each step of the study, rather, this writing in the coming sections will analyze a case study using more standardized benchmarks to evaluate beta's performance. Additionally, some academic literature exists on the necessity of using multifactor beta models, however, these models have not been widely tested and certainly not widely accepted. The major problem with this type of beta measurement is finding variables that are highly uncorrelated and since any measurements are likely to be

industry- (and perhaps company-) specific, multifactor models would not be able to provide a satisfactory starting point to screen for companies across industries. Single factor simple beta regression can be standardized in an investor's investment process and therefore *could possibly* be used as a common starting point when screening potential stocks although this paper will demonstrate otherwise.

### Limitations of Beta

While beta is fairly easy for investors to calculate, there are several limitations to beta's effectiveness as a stock picking tool including: beta's dramatic change based on news and current events, historical betas are not necessarily indicative of future beta values, and a lack of a standardized beta calculation. When new information about a company comes to market, that information can cause significant one day (or even multiple day) shifts in a company's stock price and therefore cause greater than average volatility. Patton & Verardo (2012) studied the impact of news on beta and found that:

[B]etas increase on earnings announcement days and revert to their average levels two to five days later. The increase in betas is greater for earnings announcements that have larger positive or negative surprises, convey more information about other firms in the market, and resolve greater ex ante uncertainty (p.2).

Betas do in fact change (perhaps drastically) one way or the other based on newly available information, which does change the historical regression, but the error due to the news depends on how many significant reports are released during a given time period. Additionally, betas tend to reset to their historical data which is why many investors do not "scrub" beta values for news stories.

Pablo Fernandez of the University of Navarra describes the flaws of using historical betas through focusing on the changes of beta on a day to day basis as well as investors using different timeframes to calculate beta (2012). Similar to the market overreaction to recent news and then beta retreating to historical values, sometimes stocks move erratically for no apparent reason. This erratic behavior causes historical betas to be inaccurate of their true values and if historical data is flawed, then so too will be future projections based on that data. Nonetheless, industry standard is to use historical beta as forward looking beta.

#### Leverage: Increasing Returns through Increasing Risk

The most basic definition of leverage is borrowing money from one (or potentially multiple) sources to use the money for investment elsewhere. Many retail and institutional investors alike are familiar with operating leverage and using margin to invest in securities. According to Frazzini, Kabiller & Pederson (2013), Buffett's investments use a leverage ratio of approximately 1.6:1 with the main source of cash coming from his insurance businesses including Geico. Additionally, according to the authors, "36% of Buffett's liabilities consist of insurance float with an average cost below the T-Bill rate (p.6)." Berkshire Hathaway's unique corporate structure enables Buffett to enjoy a far lower cost of capital than his peers, while also utilizing a sound, fundamental, and proven strategy for stock picking such that he makes great stock picks even better through increasing his risk and therefore his returns.

Ozdogli (2012) finds that there are "empirical patterns of market leverage, book leverage, book-to-market ratios, and stock returns across different book-to-

market portfolios (p. 1033).” Ozdagli finds that companies with a higher proportion of book value of equity to market value of equity generate greater returns than companies with a low proportion of book value of equity. The underlying theory is that companies with high relative book value of equity values generally utilize more debt than their peers. High debt levels cause an increased level of risk for the equity holders, thus equity value is less than it would be under lower debt levels. In modern portfolio theory, the equity multiplier in the ratio of a firm’s assets to its book value of equity and because debt financing is the only other way to purchase assets, companies with a greater debt levels are implicitly leveraged more than companies with less debt (Jones & Yeoman, 2012). Of course, the potential risks of debt can be somewhat lessened due to the tax deductibility of interest and so the costs and benefits must be weighed carefully. Further supporting this viewpoint is Novy-Marx (2010):

Practically, operating leverage is largely unobservable, depending not, as is often assumed, on the level of a firm’s costs and revenues (observable), but on the capitalized values of all future costs and revenues (unobservable)... In our direct tests, we show that firms with “levered” assets earn significantly higher average returns than firms with “unlevered” assets, where these characterizations refer to the level of operating (not financial) leverage (p.2).

Novy-Marx is expanding upon the idea that a firm’s use of leverage is not always easily seen by investors and that just because a firm has relatively small amounts of debt, the company can still be highly leveraged through its unobservable costs. Novy-Marx then restates one of the core assumptions of this writing – an increase in leverage generally increases the return of an investment.

#### Buffett’s Strategy: Conclusion



The first part of this article described Buffett's strategy and how investors can theoretically utilize the same methods in order to increase returns. Through the right combination of buying low beta quality stocks using leverage, an investor can increase the potential return without significantly increasing the risk. Buffett screens for companies trading at low multiples relative to the industry and overall market and then uses Berkshire's insurance business to provide leverage at a lower cost than some treasury securities.

### Methodology

To test beta's influence on investment decisions, we evaluated beta's effectiveness in predicting future stock returns through testing whether or not high beta stocks provide a superior return over time than low beta stocks as modern portfolio theory implies (see Appendix for raw data and additional detail). To start, we chose thirty stocks that are either currently or once were part of the Dow Jones Index and used the time period 1989 through 2014 to provide both historical and current contexts for our analysis. We began by calculating each company's rolling three-year beta by regressing monthly returns to the S&P 500 (which can also be calculated by dividing the asset and market covariance by the market variance; both calculations provide the same results, but the former is easier to calculate in excel). Upon calculating each company's rolling beta over the time period of the experiment (for which we used pre-1989 data for the years 1989, 1990, and 1991 to calculate the rolling three-year beta), we used the calculated beta to rank each company and then separated sorted each company into high beta, middle beta, and low beta portfolios based on the highest ten, middle ten, and lowest ten betas.

At this point, we calculated the yearly geometric returns for each portfolio, and then multiple the previous year's total return by one plus the follow year's average geometric return and compared the results to that of a yearly rebalanced portfolio. In the rebalanced portfolio, we found that the low beta portfolio performed the best (returning approximately 3099%), ahead of the middle beta portfolio (returning 2299%), the high beta portfolio (returning 1643%), and the S&P 500 (returning 741%). In the buy and hold portfolio, we found that high beta stocks outperformed middle beta, low beta, and the S&P 500 with each returning 6135%, 1824%, 1067%, and 741% respectively. We also calculated adjusted results (we adjusted by excluding data from 1999-2001 and 2007-2009 in our analysis) and found that low beta stocks finished ahead of middle beta and low beta stocks for the rebalanced portfolio and high beta stocks finished ahead of middle beta and low beta stocks in the unadjusted portfolio. The outperformance in the unadjusted portfolio can mainly be attributed to high beta stocks eventually becoming low beta stocks and not high beta stocks outperforming.

Since the buy and hold portfolio had the problems of "cherry picking" a starting date and not rebalancing during any time period based on beta reclassification, we also evaluated a buy and hold strategy using the years 1994, 1999, 2004, and 2009. In 1994, we found that high beta stocks outperformed, middle, and low beta stocks and that after adjusting for the stock market downturn in the late 1990s and late 2000s, the same order held. For 1999, high beta stock outperformed the other two portfolios on an unadjusted basis, but on an adjusted basis as well, low beta stocks were the best performers. In 2009, the middle beta

portfolio was the best performer followed by low beta stocks in second place and high beta stock in third and on an adjusted basis, this order held. In 2009 (really 2010), middle beta stocks outperformed ahead of high beta stocks and low beta stocks and on an adjusted basis, middle beta stocks were the best performers ahead of low beta stocks and then high beta stocks. This analysis demonstrated that beta is not too meaningful in evaluating investments because there is little to no consistency in the result order. Over the experiment period, we found that sometimes high beta stocks performed the best, sometime middle beta stocks performed the best, and sometimes high beta stocks performed the best with.

In the next portion of the analysis, we calculate beta's explanation of the next period's return, the next period's return in excess of a 90 day treasury bill, and the return in excess of the S&P 500 (we did each calculation on a monthly and yearly basis). Our regressions equations for both the monthly and yearly data are as follows:

- To calculate the first regression, we used the equation  $R_{it} = \alpha + \beta_1(\beta_{it-1}) + e$  where we estimate a stock's return by multiplying the beginning of the period beta by the regression's calculated beta and then add both an excess return (alpha) and a sampling error.
- To calculate the second regression, we use the return in excess of the t-bill value and set this value equal to the alpha plus the beginning of period beta multiplied by the regression's calculated beta and then adding a sampling error. This results in the equation  $Y = \alpha + \beta_2(\beta_{it-1}) + e$ .

- To calculate the third regression, we use the return in excess of the excess of the market and set this value equal to the alpha plus the beginning of period beta multiplied by the regression's calculated beta and then adding a sampling error. This results in the equation  $Y = \alpha + \beta_3(\beta_{it-1}) + e$ .
- To calculate the fourth regression, the expected return regression, we utilize the beginning of the period beta multiplied by the end of the period actual S&P 500 return, we use the equation  $Y = \alpha + \beta_4(\beta_{it-1} * r_{mkt}) + e$ .

Additionally, for each period we also calculated the estimated return by multiplying the beginning of the month beta by the actual S&P 500 return for that time period. For the monthly analysis, we use each stock's beginning of the month beta (starting at the beginning of 1989) and used each stock's end of month return. In the basic regression, we found the estimated r-squared value to be 0.715% which is greater than the actual r-squared value of 0.168%. R-squared is the percentage of the "y" value (in this case returns) that is explained by the "x" value (in this case beta) and since both r-squared values result in values of less than 1%, the analysis indicates very low predictive power of beta. In the excess t-bill returns, the actual r-squared value was 0.167% and the estimated r-squared value was 0.712% and in the excess market regression, the actual r-squared value was 0.132% and the estimated value was 1.96%. Since the r-squared values were so low in each case, this indicated that beta has little to no return explanatory power and evaluating the yearly data shows a similar story to that of the monthly results.

In the simple yearly regression, the actual r-squared value was 0.944% which was significantly lower than the estimated r-squared value of 5.28%, but in

both cases, beta showed minimal predictive ability. In the excess t-bill return (we used annualized t-bill returns), the actual r-squared value was 0.941% compared to the estimated value of 5.29% and in the excess S&P 500 returns resulted in an actual r-squared of 0.902% and an estimated r-squared value of 17.69%. Similar to the monthly results, beta showed little to no explanatory ability in the actual returns, but did show better explanatory ability in the estimated returns. However, any investor hope in using yearly betas to estimate returns moving forward should use caution due to the gap between estimated and actual explanatory value.

After calculating beta's ability to predict returns, we then looked to find the relationship between each variable in our analysis (arithmetic return, geometric return, beta, and standard deviation) on a monthly and yearly basis. The relationship between standard deviation and arithmetic return (using standard deviation as the explanatory variable) resulted in an r-squared value of 16.2% compared to the standard deviation and geometric return r-squared value of 9.64%. The relationship between beta and arithmetic return resulted in an r-squared value of 10.44% and the relationship between beta and geometric return resulted in an r-squared value of 5.15%. The r-squared value between beta and standard deviation was 64.9% and these data indicate that while there is a low (albeit better than the analysis above) relationship between beta and return, there is a fairly strong relationship between beta and risk (standard deviation). However, there appears to be little relationship between risk and return and if high beta stocks can produce the same returns as low beta stocks, an investor should buy the low beta stocks to have less risk. Based on this portion of the analysis, beta

can influence investors who have an interest in measuring risk in addition to return because there is a relationship between beta and risk.

On a yearly basis, standard deviation and arithmetic return resulted in an r-squared value of 61.57% and an r-squared value of 4.04% on a standard deviation and geometric basis. The strong relationship between standard deviation and arithmetic return is likely due to the outperformance during strong years being greater than that of underperformance and also partially due to not evaluating *totally* returns (as in the geometric return analysis). The r-squared value for beta and arithmetic return was 10.69%, for beta and geometric return was 4.42%, and for beta and standard deviation was 43.17%. On a yearly basis, there is a stronger relationship between beta and arithmetic return than in the monthly analysis, but on a geometric return basis, the relationship is less than half of the monthly value. Also, the relationship between beta and standard deviation was more than 20% less than that of the monthly test which indicates a far weaker relationship between risk and beta. In sum, while there may be some relationship between beta and risk in the monthly experiment, when evaluating yearly data, that relationship significantly wanes.

### Conclusion

Based on the above analysis portfolios based on historical betas as well as regressing each company's returns (and excess returns) from 1989 through 2014, beta could potentially play a role in making investment decisions. With no clear relationship between beta and return over for this data set, beta appears to be the result of other factors and not too useful on a standalone basis in this capacity.

However, if an investor is evaluating risk, beta appears to be more useful depending on the time period of returns used (monthly beta had a far greater relationship with risk than yearly). The challenge is overcoming the similarity in middle beta and low beta companies and trying to find key differences. For example, both middle beta and low beta companies are mainly manufacturing companies, consumer staple companies, and other large industrial companies, whereas most of the high beta companies are technology and/or entertainment firms. While the middle beta and low beta companies have consistently performed well over many years, an investor buying mostly these types of companies may not have the optimal portfolio mix because they are forgoing the benefits of outperformance of high beta stocks during strong economic periods. Additionally, many high beta stocks do outperform over time and are just as “safe” as the middle and low beta stocks. For example, Apple and American Express have higher than average betas, but both have performed very well and have a strong future outlook regardless of the economic cycle (American Express has run into a little bit of trouble over the past four months, but that’s in the near term and American Express has done very well for a number of years). Over time, the High Beta Portfolio has been in line with the S&P 500 and choosing it over the S&P may be a good idea if the high beta companies either pay dividends or have a strong track record. If the companies in the high beta portfolio have a short track record, they may be the next Apple, Google, or Microsoft, but will likely be the next Pets.com or another perennial underperformer.

While Beta is interesting to look at and something that investors should be aware of, there are many better metrics to evaluate stocks and influence investor decisions. For example, looking at price-to-earnings, price-to-book, and eps growth can all better influence investment decisions than beta. Beta should play a minimal role in investing and by screening for more influential criteria, an investor will more likely be able generate similar (if not better) returns as the Middle Beta Portfolio in this analysis.

Unfortunately, for retail investors, beta represents a data point of mixed influence and cannot help in evaluating returns, but can help in measuring risk. Additionally, as demonstrated above, while there is a relationship between beta and risk (albeit minimal) there is no relationship between risk and return. If risk and return are unrelated, an investor is better off determining their investment objectives and then setting up a process to achieve their individual goals. For example, if investors are interested in earning a higher return with little attention to risk, then they should focus on predicting future returns whereas if an investor is interested in reducing risk, then the investor should evaluate a stock's beta. Furthermore, since beta estimations are available through many sources in the public domain (Yahoo! Finance, Google Finance, Reuters, Bloomberg, etc.), individual investors should have fairly easy access to the data and can incorporate beta if they so choose.



## Appendix A

### Simple Monthly Regression

SUMMARY OUTPUT: Actual

Regression Statistics	
Multiple R	0.094974732
R Square	0.0090202
Adjusted R Square	0.007746447
Standard Error	0.288723452
Observations	780

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.590330294	0.590330294	7.081592751	0.007948541
Residual	778	64.85503821	0.083361232		
Total	779	65.4453685			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.004536487	0.023143775	-0.196013275	0.844650961	-0.04996813	0.040895156	-0.04997	0.040895
X Variable 1	0.054423238	0.020451205	2.661126219	0.007948541	0.014277157	0.094569318	0.014277	0.094569

SUMMARY OUTPUT: Estimated

Regression Statistics	
Multiple R	0.42068814
R Square	0.176978511
Adjusted R Square	0.175920643
Standard Error	0.0860059
Observations	780

ANOVA

	df	SS	MS	F	Significance F
Regression	1	1.237500692	1.237500692	167.2973108	8.40902E-35
Residual	778	5.754877552	0.007397015		
Total	779	6.992378243			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.076012544	0.006894144	-11.02566745	2.28963E-26	-0.089545873	-0.062479216	-0.08955	-0.06248
X Variable 1	0.078796978	0.006092073	12.93434617	8.40902E-35	0.066838131	0.090755826	0.066838	0.090756

### Monthly Return Excess TBill

SUMMARY OUTPUT: Actual

Regression Statistics	
Multiple R	0.040958923
R Square	0.001677633
Adjusted R Square	0.001570952
Standard Error	0.08592488
Observations	9360

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.116103994	0.116103994	15.72567488	7.37689E-05
Residual	9358	69.09090904	0.007383085		
Total	9359	69.20701304			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.001556568	0.001982079	0.785320763	0.432285406	-0.002328738	0.005441874	-0.002328738	0.005441874
X Variable 1	0.006937494	0.001749436	3.965561105	7.37689E-05	0.00350822	0.010366768	0.00350822	0.010366768

SUMMARY OUTPUT: Expected

Regression Statistics	
Multiple R	0.084388938
R Square	0.007121493
Adjusted R Square	0.007015393
Standard Error	0.047164389
Observations	9360

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.149309143	0.149309143	67.12093113	2.88871E-16
Residual	9358	20.81668023	0.00222448		
Total	9359	20.96598937			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.002803436	0.001087968	-2.576762172	0.00988231	-0.00493609	-0.000670781	-0.00493609	-0.000670781
X Variable 1	0.007867237	0.00096027	8.192736486	2.88871E-16	0.005984899	0.009749575	0.005984899	0.009749575

## Monthly Return Excess Market

SUMMARY OUTPUT: Actual

Regression Statistics	
Multiple R	0.036397526
R Square	0.00132478
Adjusted R Square	0.001218061
Standard Error	0.07510373
Observations	9360

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	0.070020549	0.070020549	12.41373581	0.000428221
Residual	9358	52.78445684	0.00564057		
Total	9359	52.85447739			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.001538093	0.001732461	-0.88786829	0.3746667	-0.004934094	0.001857907	-0.004934094	0.001857907
X Variable 1	0.005387556	0.001529116	3.523313187	0.000428221	0.002390155	0.008384957	0.002390155	0.008384957

SUMMARY OUTPUT: Expected

Regression Statistics	
Multiple R	0.140190302
R Square	0.019653321
Adjusted R Square	0.01954856
Standard Error	0.022653367
Observations	9360

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	0.096273067	0.096273067	187.6027926	2.70936E-42
Residual	9358	4.802291845	0.000513175		
Total	9359	4.898564912			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.005898097	0.000522558	-11.28696341	2.35484E-29	-0.006922425	-0.004873769	-0.006922425	-0.004873769
X Variable 1	0.006317299	0.000461224	13.69681688	2.70936E-42	0.0054132	0.007221398	0.0054132	0.007221398

## Yearly Simple Regression

SUMMARY OUTPUT: Actual

Regression Statistics	
Multiple R	0.097165482
R Square	0.009441131
Adjusted R Square	0.008167919
Standard Error	0.334283012
Observations	780

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	0.828613376	0.828613376	7.415207824	0.006612372
Residual	778	86.93771257	0.1111745132		
Total	779	87.76632595			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.081312581	0.026795782	3.034529098	0.002489326	0.028711982	0.13391318	0.028711982	0.13391318
X Variable 1	0.064478186	0.023678334	2.723087921	0.006612372	0.017997193	0.110959178	0.017997193	0.110959178

SUMMARY OUTPUT: Estimated

Regression Statistics	
Multiple R	0.229945563
R Square	0.052874962
Adjusted R Square	0.051657578
Standard Error	0.190335079
Observations	780

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	1.573475625	1.573475625	43.433252	8.08489E-11
Residual	778	28.18495002	0.036227442		
Total	779	29.75842564			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.009836524	0.015257064	0.644719317	0.519299147	-0.020113365	0.039786413	-0.020113365	0.039786413
X Variable 1	0.088851926	0.013482042	6.590390883	8.08489E-11	0.062386437	0.115317415	0.062386437	0.115317415

## Yearly Return Excess TBill

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.097025689
R Square	0.009413994
Adjusted R Square	0.008140737
Standard Error	0.331979428
Observations	780

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	0.814860406	0.814860406	7.393683789	0.006691193
Residual	778	85.74364474	0.11021034		
Total	779	86.55850515			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.049464312	0.026611129	1.858782882	0.063435342	-0.00277381	0.101702434	-0.00277381	0.101702434
X Variable 1	0.063940836	0.023515164	2.719132911	0.006691193	0.01778017	0.110101542	0.01778017	0.110101542

Regression Statistics	
Multiple R	0.230173799
R Square	0.052979978
Adjusted R Square	0.051762729
Standard Error	0.188985963
Observations	780

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	1.55450207	1.55450207	43.52434149	7.73622E-11
Residual	778	27.78681007	0.035715694		
Total	779	29.34131214			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.022011745	0.01514892	-1.453024036	0.146620289	-0.051749347	0.007725856	-0.051749347	0.007725856
X Variable 1	0.088314597	0.01338648	6.597298045	7.73622E-11	0.062036698	0.114592496	0.062036698	0.114592496

## Yearly Return Excess Market

SUMMARY OUTPUT: Actual

Regression Statistics	
Multiple R	0.094974732
R Square	0.0090202
Adjusted R Square	0.007746447
Standard Error	0.288723452
Observations	780

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	0.590330294	0.590330294	7.081592751	0.007948541
Residual	778	64.85503821	0.083361232		
Total	779	65.4453685			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.004536487	0.023143775	-0.196013275	0.844650961	-0.04996813	0.040895156	-0.04997	0.040895
X Variable 1	0.054423238	0.020451205	2.661126219	0.007948541	0.014277157	0.094569318	0.014277	0.094569

SUMMARY OUTPUT: Estimated

Regression Statistics	
Multiple R	0.42068814
R Square	0.176978511
Adjusted R Square	0.175920643
Standard Error	0.0860059
Observations	780

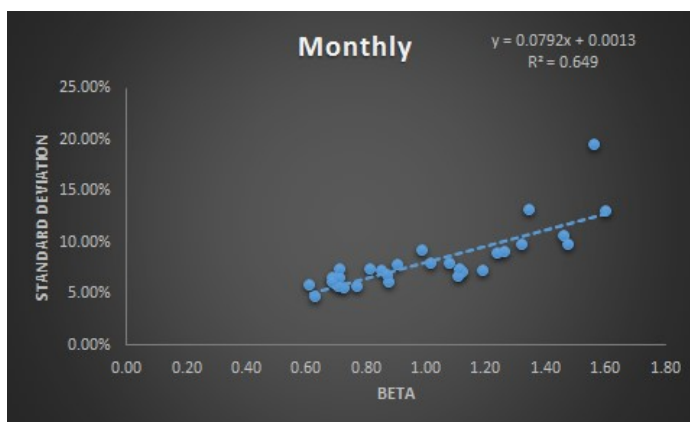
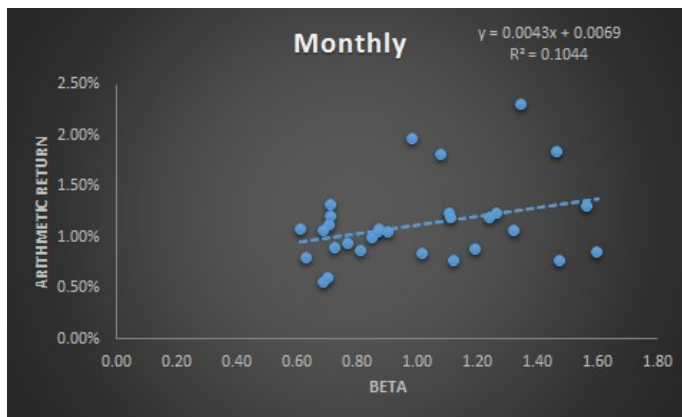
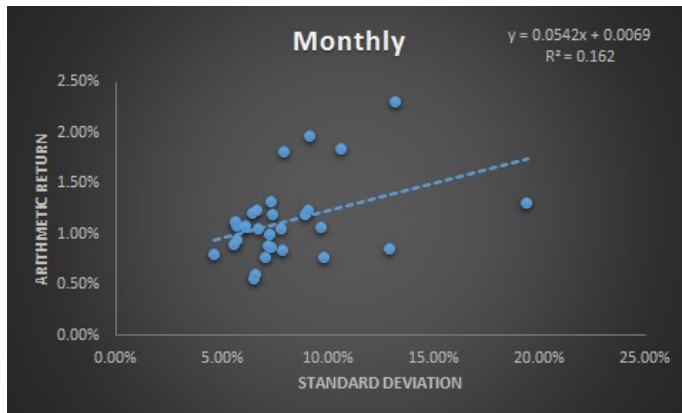
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	df	SS	MS	F	Significance F
Regression	1	1.237500692	1.237500692	167.2973108	8.40902E-35
Residual	778	5.754877552	0.007397015		
Total	779	6.992378243			

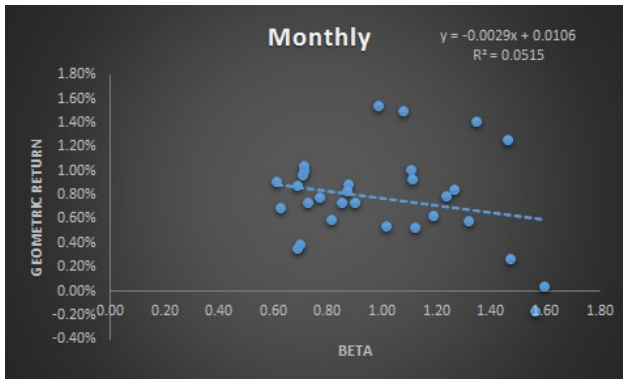
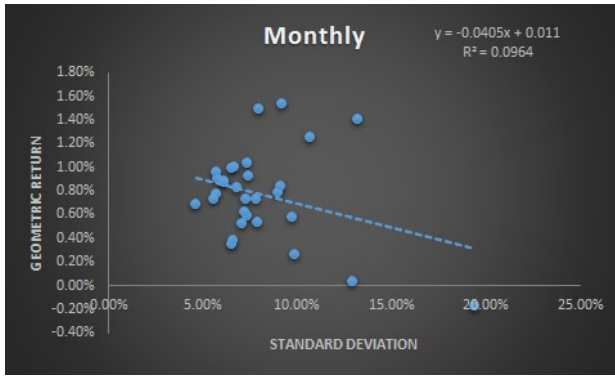
  

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X Variable 1	0.078796978	0.006092073	12.93434617	8.40902E-35	0.066838131	0.090755826	0.066838	0.090756

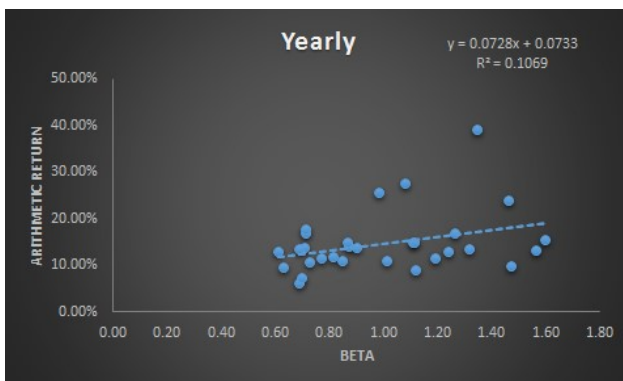
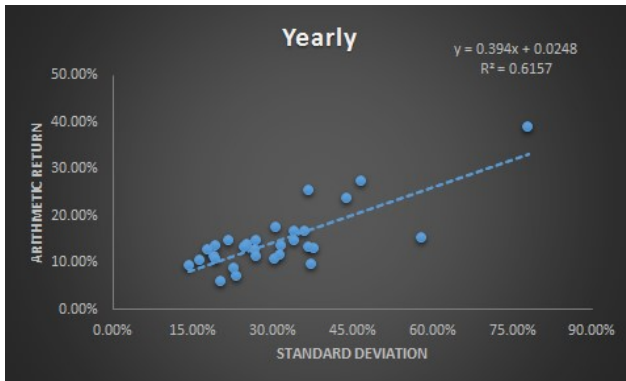
Appendix B

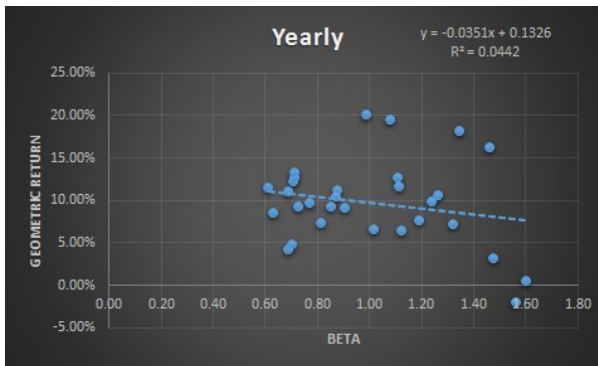
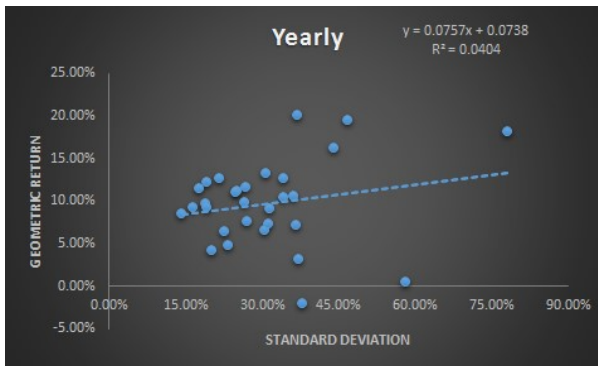
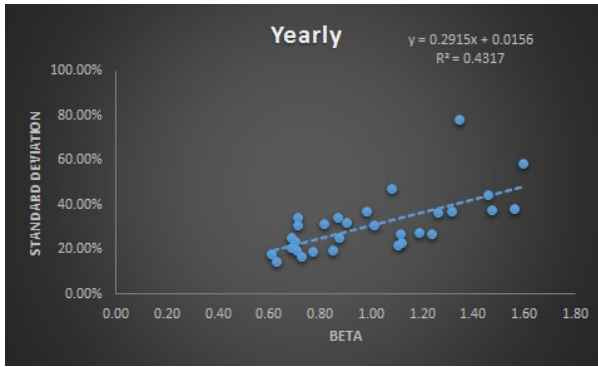
Monthly





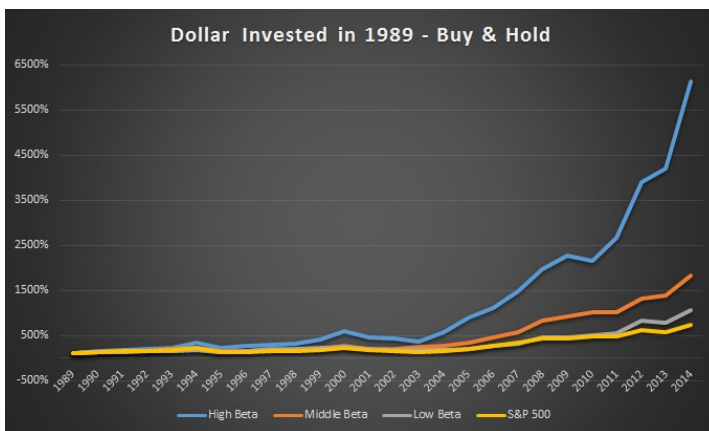
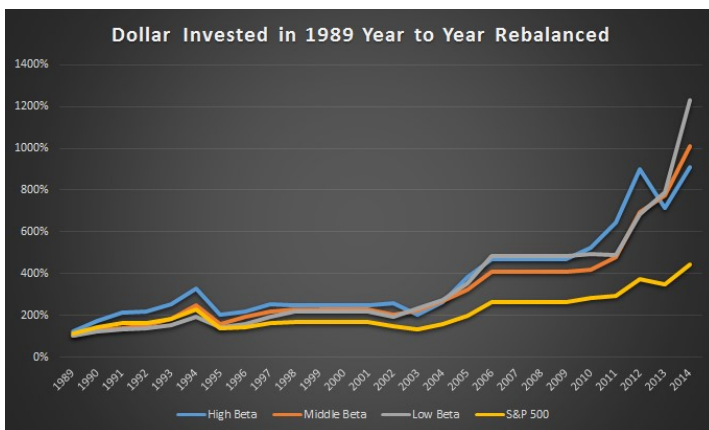
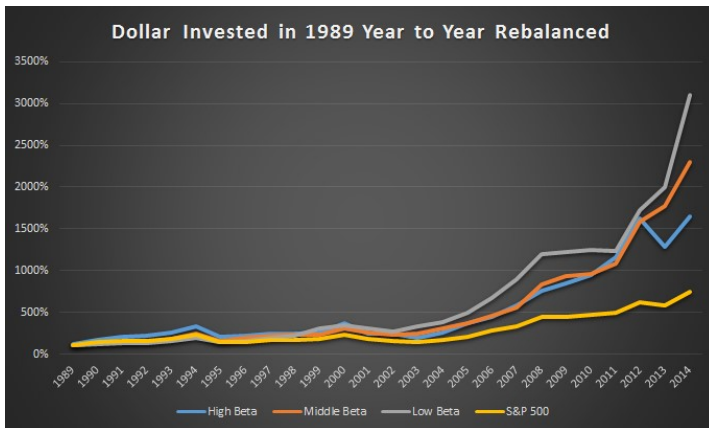
Yearly

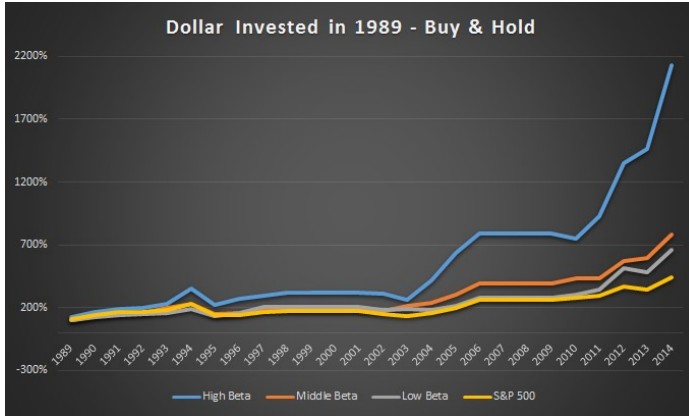




Appendix C

\$1 Invested







### References

- Adrego Pinto, A. (2014). Financial Bubbles. In Modeling, Dynamics, Optimization and Bioeconomics I Contributions from ICMOD 2010 and the 5th Bioeconomy Conference 2012 (Aufl. 2014 ed., Vol. 73, pp. 454-455). New York: Springer International Publishing.
- Black, F. (1993). Beta And Return. *The Journal of Portfolio Management*, 8-18.
- Chor, D., & Manova, K. (2011). Off the cliff and back? Credit conditions and international trade during the global financial crisis. *Journal of International Economics*, 117-133.
- Chen, L., He, S., & Zhang, S. (2011). When all risk-adjusted performance measures are the same: In praise of the Sharpe ratio. *Quantitative Finance*, 11(10), 2-2.
- Clarke, R., Silva, H., & Thorley, S. (2010). Minimum-Variance Portfolio Composition. *The Journal of Portfolio Management*, 31-45.
- Cornell, B. (2010). Economic Growth and Equity Investing. *Financial Analysts Journal*, 66(1), 54-64.
- Dahl, C., & Iglesias, E. (2011). Modeling the Volatility-Return Trade-Off When Volatility May Be Nonstationary. *Journal of Time Series Econometrics*.
- Damodaran, A. (2013). Living with Noise: Valuation in the Face of Uncertainty. *CFA Institute Conference Proceedings Quarterly*, 22-36.
- Estrada, J. (2013). Are stocks riskier than bonds? Not if you assess risk like Warren Buffett. *Journal of Asset Management*, 73-78.

- Fernandez, P. (2012). Ten Badly Explained Topics in Most Corporate Finance Books. 1-12.
- Frazzini, A., & Pedersen, L. (2013). Betting against beta. *Journal of Financial Economics*, 111, 1-25.
- Frazzini, A., Kabiller, D., & Pederson, L. (2013). Buffett's Alpha. *Social Science Research Network*, 2-5.
- Gardiner, J. (Director) (2009, November 12). TRANSCENDENT LEADERSHIP: BOARD METRICS FOR PROFITS, PEOPLE, AND PLANET . Paper presented at the Annual Meeting of the International Leadership Association, Prague, Czech Republic, November 12, 2009.. Lecture conducted from International Leadership Association, Prague, Czech Republic.
- Gray, W., & Vogel, J. (2011). Analyzing Valuation Measures: A Performance Horse-Race Over the Past 40 Years. CFA Institute, 1-5.
- Guo, W., Wang, F., & Wu, H. (2011). Financial leverage and market volatility with diverse beliefs. *Economic Theory*, 337-364.
- Hanson, D., & Fraser, J. (2013). ESG Investing in Graham & Doddsville. *Journal of Applied Corporate Finance*, 25(3).
- Jones, S., & Yeoman, J. (2012). Bias in estimating the systematic risk of extreme performers: Implications for financial analysis, the leverage effect, and long-run reversals. *Journal of Corporate Finance*, 1-21.

- Keller, W. (2014). Momentum, Markowitz, and Smart Beta. Social Science Research Network, 0.9. Retrieved November 18, 2014, from [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2450017](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2450017)
- Meng, R. (2008). A patent race in a real options setting: Investment strategy, valuation, CAPM beta, and return volatility. *Journal of Economic Dynamics and Control*, 3192-3217.
- Novy-Marx, R. (2010). Operating Leverage. *Review of Finance*, 15(1), 103-134.
- Ozdogli, A. (2012). Financial Leverage, Corporate Investment, and Stock Returns. *Review of Financial Studies*, 1033-1069.
- Patton, A., & Verardo, M. (2012). Does Beta Move with News? Firm-Specific Information Flows and Learning about Profitability. *Review of Financial Studies*, 25(9), 2789-2839.