Examining the Low Volatility Anomaly in Stock Prices

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Examining the Low Volatility Anomaly in Stock Prices

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By
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ABSTRACT

Modern portfolio theory states that investments with greater beta, a common measure of risk, require greater returns from investors in order to compensate them for taking greater risk. Therefore, under the premise that market participants act rationally and therefore markets run efficiently, investments with higher beta should generate higher returns vis-à-vis investments with lower beta over the long run. In fact, many studies suggest that investments with lower beta actually generate equal to or higher returns relative to investments with higher beta. In looking at data for the S&P 500 going back 22 years between 1990 and 2012, this study found that there was very low correlation between beta and returns. In fact, portfolios with very low risk generated commensurate to better returns versus portfolios with very high beta. Therefore, we find that beta appears to be a poor measure of risk as it relates to the stock market.

In addition to beta and returns, this study looked at the fundamental characteristics of each company specifically corporate profitability and balance sheet leverage which are commonly used by investors in assessing the underlying quality of a company. We find that companies with higher levels of return on equity combined with lower levels of balance sheet leverage tend to outperform companies with lower levels of
profitability and higher balance sheet leverage. As a result, we find a high correlation between balance sheet leverage, ROE and stock returns. This paper suggests that in fact, fundamental factors such as leverage and ROE tend to be better measures of risk vis-à-vis beta. One important final observation is the fact that while in general, companies with high ROEs and low leverage tend to outperform companies with low profitability and high leverage, portfolios of those companies with the highest ROE and lowest leverage and portfolios of those companies with the lowest ROE and highest leverage actually underperform on the whole other portfolios. In other words, portfolios of companies that exhibit the most extreme of characteristics in terms of ROE and leverage underperform portfolios of companies with more moderate characteristics.

One plausible explanation for these observations is rooted in behavioral economic theory known as the favorite long shot bias and the opposite favorite long shot bias. The opposite favorite long shot bias suggests that market participants tend to “over-bet” an asset and/or an investment with high probability of a payoff but low overall return if the payoff occurs (ie the sure bet). In fact, market participants go so far to secure a payoff that they actually place a higher bet on the probability of success than the actual odds would suggest. In stock market terms, investors will tend to over-value the least-riskiest stocks to the point where risk and return is no longer favorable. Similar phenomenon can be observed in horse race betting and sports drafts. The favorite long shot bias is the inverse of the opposite favorite longshot bias. This theory suggests that market participants actually “over bet” an asset and/or an investment with the lowest probability
of a payoff but with significant overall returns if the payoff occurs. Similar phenomenon takes place in the purchase of insurance to insure against large potential losses with small probabilities as well as lottery ticket purchases.

We see the most striking evidence of this when looking at the returns of stocks with the highest ROEs and the lowest levels of debt/capital as of 1990. In that year, investors would have based their investments in stocks using current attributes at that time. We can see that stocks with the highest ROEs and lowest levels of debt/capital garner higher valuations relative to the broad stock market. We also see that stocks with the lowest ROEs and highest debt/capital also command premium valuations to the market as a whole. Therefore, risk-averse investors will tend to overvalue companies with the least risky prospects while risk loving investors will tend to overvalue companies with the riskiest prospects at the same time. As a result, we can see from looking at the future returns that companies that exhibit extreme characteristics in terms of ROE and debt/capital tend to underperform the broad market. Similar to high profile athletes and horse track betting, we find that investors tend to over-bet sure shot investments while simultaneously over-betting long shot investments.
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EXAMINING THE CAPITAL ASSET PRICING MODEL

Modern portfolio theory suggests that an asset’s returns relative to other assets or asset classes should be commensurate with the risks an investor assumes when investing in that asset relative to the risks of investing in other assets or asset classes. The Capital Asset Pricing Model (CAPM) is the most commonly used model in defining an asset's expected returns relative to an asset's respective risks. This simple model initially derived to help explain individual stock returns and portfolios of stocks was first introduced by Jack Treynor, William Sharpe, John Lintner and Jan Mossin in the early

**Figure 1**

**CAPITAL ASSET PRICING MODEL (CAPM)**
1960s and was built on the back of Harry Markowitz’s work on modern portfolio theory and diversification often called the “mean-variance model” used for predicting a portfolio’s future returns. This model is widely used in applications such as estimating the cost of capital for firms and evaluating the performance of managed portfolios. The attraction of the Capital Asset Pricing Model is that it offers pleasing and simple predictions about how to measure risk and the relationship between expected return and idiosyncratic risk. Under CAPM, volatility and risk are measured by a stock’s beta versus a stock market benchmark such as the S&P 500 Index. For example, a stock that moves two or three times more in magnitude than the direction of the S&P 500 on a daily basis over a certain period of time is considered to hold higher beta and therefore has higher volatility than a stock that moves in-line with magnitude of the S&P 500 on a daily basis or over the same time horizon. The Capital Asset Pricing Model looks at an asset’s expected return as a function of that asset’s beta relative to the beta of some benchmark index plus the risk free rate of return available to investors in the marketplace. For example, a stock with a beta of 1.5x relative to the S&P 500 in an environment where the risk free rate of return on US government securities is 5% and the average return on the market is 8% would yield an expected return of 9.5% [Equation: Expected Return = Risk Free rate + Beta (S&P 500 return – Risk Free Rate of Return or 5% + 1.5 (8%-5%) = 9.5%]. The basic idea is that a stock with higher volatility relative to the broader stock market should compensate investors with higher relative returns versus the stock market over a long period of time relative to a stock with lower volatility versus the broader market. As a rational investor, why take higher risk if one isn’t compensated with
higher returns? As a result of incurring this higher volatility, an investor should expect higher returns over time.

Before going further, it is important to understand and define what beta actually represents. Beta is calculated using regression analysis over a specified time frame and is measured relative to an index. In most cases, stock price beta is measured relative to the S&P 500 which is the most commonly used proxy for the market as a whole. Stocks with a beta greater than 1 have greater volatility than the overall market. Stocks with a beta equal to 1 have similar volatility to the market as a whole and stocks with a beta of less than 1 have lower volatility relative to the market. Statistically, the beta of an investment measures how it co-varies with the market portfolio, in the case the S&P 500. In other words, beta measures the correlated volatility of an asset relative to the volatility of an underlying benchmark or how an asset co-varies relative to its benchmark or a chosen benchmark. Since beta is measured relative to a market index, the risk surrounding beta is often called non-diversifiable risk. Non-Diversifiable risk the risk an investor assumes which cannot be mitigated at all, often called market risk. This is the part of an asset’s statistical variance that cannot be removed by the diversification provided by a portfolio of many risk assets. Diversifiable risk, on the other hand, is risk that can be mitigated, but not necessarily eliminated, by investing across different companies in different sectors across different asset classes and different geographies. The point here is to minimize the risk of huge loss from taking the whole risk against one or a few companies, sectors, assets and countries.
Unfortunately, the empirical record of the Capital Asset Pricing Model is poor. Recent studies on high and low volatility portfolios suggest just the opposite in that high-beta high volatility stocks actually underperform low-beta low volatility stocks over the long term. This has been called the Low Volatility Anomaly in that the fact that investors can earn higher returns while taking lower risk challenges modern portfolio theory and rational expectations assumptions. In the words of Harin de Silva, investors are getting a “Free Lunch” by generating excess returns to the market while taking lower risks than portfolio theory suggests. This is an important observation and a profound departure from Efficient Market Theory, also dubbed Random Walk Theory by Burton G Malkiel in his popular book “A Random Walk Down Wall Street.” Random Walk theory suggests that the market disseminates all information and salient news on stocks quickly and accurately in terms of its impact on a stock’s intrinsic value. By definition, intrinsic value refers to the actual value of a company or an asset based on an underlying perception of its true value in terms of both tangible and intangible factors. This value may or may not be the same as the current market value as determined by the market. According to Malkiel, a company’s intrinsic value will be fully reflected in its stock price with respect to risk and return leaving investors little excess profits over the broad market. Thus, over the long run active investors cannot beat aggregate stock market returns given markets are believed to be perfectly efficient (Malkiel 53). The major assumption here is that all investors, who are basically constituents of the market, act rationally in terms of how they process information about stocks and that all investors are risk averse in terms of looking for the best risk-return tradeoff based on available
investment opportunities. In fact, as Nate Silver reflects in his book, The Signal and the Noise,

“The efficient-market hypothesis is intrinsically somewhat self-defeating. If all investors believed the theory – that they can’t make any money from trading since the stock market is unbeatable – there would be no one left to make trades and therefore no market at all.” (Silver 156)

In other words, the fact that there are markets and investors that constitute markets suggests that profit opportunities exist and that the movements and trends that underlie markets are subject to the same rational and irrational decisions made by the collective actions of individual investors every day. Along these lines, the idea that low volatility low beta stocks actually outperform high volatility high beta stocks suggests that the relationship between risk and reward is not perfectly linear as Modern Portfolio Theory would suggest but that investors’ marginal aversion to risk may in fact change as an investor assumes more or less risk.

A number of studies have looked at the low volatility anomaly in great depth to try to understand whether in fact the anomaly exists and whether this low volatility anomaly could be influenced by other factors such as country bias, size effect, value versus momentum strategies, etc. In the 1970s, Black, Jensen and Scholes and Robert A. Haugen and A. James Heins found that the relationship between risk and return was flatter than those predicted by the Capital Asset Pricing Model. Haugen and Heins constructed sample portfolios from stocks selected from those listed on the New York Stock Exchange from 1926 to 1971. Each portfolio consisted of 25 stocks for a total of

5
114 portfolios. No attempts were made to prescreen the stocks to assure their survival over the period observed so that survivorship bias was eliminated. From the relative monthly performance for the 114 portfolios, they calculated geometric mean returns and standard deviation of the monthly returns over the entire 46-year period and nine shorter periods of five years. Based on their results, they concluded that in fact no risk premium exists for risking taking in the stock market and therefore that the conventional hypothesis that risk, systematic or otherwise, generates a special reward was not observed in their results. (Heins, Haugen, James 9) In other words, as investors assumed higher risk their return profile did not improve enough to compensate them for the additional risk taken as predicted by CAPM. The traditional Capital Asset Pricing Model suggests a
linear straight line starting from the risk free rate of rate with zero-beta running up and to the right suggesting that expected stock returns improve as beta increases. If actual stock returns were lower than those expected by CAPM, then this would suggest that either investors place a greater than necessary penalty on stocks which exhibit higher volatility or that investors tend to overestimate the returns on high beta stocks and/or underestimate the returns on low beta stocks which would violate rational expectations, a key assumption in the CAPM.

Haugen and Heins went so far as to suggest that CAPM is not just flatter than predicted but actually inverted in their shorter 5 year sample periods suggesting that investors could actually make positive returns by investing in low risk stocks while generating negative returns in high risk stocks such that not only were investors penalized for taking greater risk but they were actually rewarded for taking lower risk during that sample period. (Heins, Haugen, James 9) In 1992, Eugene Fama and Kenneth French looked at data from 1941 through 1990 suggesting a similar flat CAPM curve relative to expectations. According to Fama and French, regression models used to test CAPM have consistently shown that the coefficient on beta is less than the average excess market return which in this case is proxied as the average return on a portfolio of US common stocks minus the Treasury bill rate. (French, Fama 53)

The intercepts in time series regressions of excess asset returns and the excess market return are positive for assets with low betas and negative for assets with high
betas. In fact, based on Fama and French’s work, the predicted return on the portfolio with the lowest beta is 8.3% per year while the actual return is 11.1%. The predicted return on the portfolio with the highest beta is 16.8% per year while the actual return is 13.7%. Fama and French concluded that the variation in expected return is unrelated to market beta and went so far as to suggest that ratios such as book value to market equity, earnings to price ratios and earnings to cash flow ratios actually do a better job of explaining stock returns than beta and CAPM. (French, Fama 53) More recently, Clark, de Silva and Thorley looked at minimum variance portfolios between 1968 and 2005. Based on the 1,000 largest US stocks over that period, the authors found that minimum variance (i.e. those with the lowest beta relative to the market) portfolios achieved a volatility reduction of 25% relative to the broader stock market while delivering comparable, or even higher, average returns over that time noting that low volatility actually produced commensurate better returns than an equivalent size portfolio of high volatility stocks. In fact, the average monthly returns for the lowest volatility portfolio were ~1% between 1968 and 2005 while the average monthly standard deviation was ~3.7%. This, according to the authors, was in stark contrast to the highest volatility portfolio which generated monthly average returns of ~0.8% with an average monthly standard deviation of ~8.8%. Furthermore, the 2nd quintile portfolio in terms of lowest volatility carried similar monthly returns to the lowest volatility portfolios but with 33% greater average monthly volatility. The 3rd and 4th quintile portfolios also generated similar average monthly returns but with 50% and 85% greater average monthly standard deviation respectively. Therefore, the authors found that there was no
return premium for assuming higher risk as predicted by CAPM (Clark, de Silva Thorley 43). In addition, in 2006 Andrew Ang, Robert J. Hodrick, Yuhang Xing and Xiaoyan Zhang looked at stocks across 23 developed markets and the difference in average returns between extreme quintile portfolios sorted by idiosyncratic volatility. The study controlled for factors including world market, size and value factors and ruled out explanations such as trading frictions, information dissemination and higher moments. They concluded that stocks with recent past high idiosyncratic volatility tend to have much lower returns than stocks with recent past low volatility with respect to local, regional and world stock markets. In their results, there was a statistically significant difference between the returns of the highest and lowest quintile portfolios when sorted by volatility. (Ang, Hodrick, Xing, Zhang 23) In addition, in 2007 David Blitz and Pam van Vliet looked at the alpha spread of low versus high volatility portfolios on a global basis and concluded that the lowest decile volatility portfolios outperformed the highest decile volatility portfolios by 12% between 1986 and 2006. Similar to Ang, Hodrick, Xing and Zhang, this study controlled for geography, size bias and strategy bias (i.e. value versus growth or value versus momentum) and concluded that low volatility portfolios still outperformed high volatility portfolios in a statistically significant manner. Their results showed that the difference in absolute returns between top and bottom decile volatility portfolios was 5.9%. Interestingly, the authors noted that while low volatility portfolios underperformed high volatility portfolios in months with positive market returns and outperformed high volatility portfolios in months with negative market returns, the amount by which low volatility portfolios underperformed in up
market months was much less than the amount by which they outperformed in down market months. Furthermore, when controlling for size and value effects, their studies suggested that about one third of the alpha spread disappeared but still low volatility portfolios outperformed high volatility portfolios by 8.1% and this positive alpha spread was consistent across all geographies. (Blitz, Van Vliet 102-113)

In a separate study conducted in August 2012 by the S&P Dow Jones Indices, Aye M. Soe, Director of Index Research & Design suggests that the “low volatility effect” challenges traditional equilibrium asset pricing theory (CAPM) that higher risk securities should be rewarded with higher expected returns while lower-risk assets receive lower returns over a sufficient period of time. According to Aye’s research, over a 10-year period of time end on March 31, 2012, the S&P 500 Low Volatility Index returned 6.95% with 10.75% standard deviation while the Minimum Volatility Index returned 5.1% with 12.32% standard deviation. Both of these relatively low volatility indexes generated superior returns to the broader S&P 500 Index that returned 4.12% with 15.99% standard deviation. In other words, by investing in a basket of low-risk risk stocks as defined by their implied beta to the market, an investor can generate 24% to 68% higher returns while assuming 23% to 34% lower volatility. In addition, there was no market capitalization bias in Aye’s study. In looking at large, medium and small size companies, over a medium to long term time horizon, the low volatility is indeed present across all three attributes although the low volatility effect is strongest and most evident across the large capitalization categories and weakest across the smaller market.
capitalization category. In addition, Aye’s research suggested asymmetric returns across low-volatility strategies in their ability to capture up and downside returns. Similar to Blitz and Vliet, Aye observed that low volatility strategies tend to underperform high volatility strategies when markets are trending upwards and outperform high volatility strategies when markets are trending downwards. Importantly, though, low volatility strategies underperformed less in upward trending markets than they outperformed in downward trending markets. Low volatility strategies underperformed by approximately 0.55% to 1.7% during up market periods depending on market capitalization but outperformed by 1.4% and 2.5% during down markets. On average, low-volatility strategies outperformed their respective market benchmarks in 47-50% of the months studied but low-volatility strategies outperformed less frequently when the market trended upward and outperformed markets approximately 73% to 87% of the times when market returns were negative. This asymmetric response to market movement highlights the ability of low-volatility strategies to provide downside protection in uncertain times. Taken together, low volatility strategies possess asymmetric risk-return profiles in that they outperform more frequently and with larger magnitude when the market is trending down. (Soe 5)
THE EMPIRICAL EVIDENCE SURROUNDING CAPM AND BETA

The purpose of this study is to look at the S&P 500 returns over a sufficiently long period of time in order to determine whether this low volatility effect has held and what other distinctions we can draw between high and low volatility portfolios in addition to other aspects of stocks that may influence returns versus simply volatility. Specifically, I took the individual constituents of the Standard & Poor’s 500 Index over a period of 22 years beginning from 1990 and ending in 2012. The Standard & Poor’s 500 is an equity index most commonly used as a benchmark proxy for investment managers. The Standard and Poor’s index is a free-float capitalization-weighted index based on the common stock prices of 500 US companies. The index consists of both value stocks and growth stocks and in general has a bias towards companies with larger market capitalizations. The constituents of the S&P 500 are selected by committee that select those companies to be included in the index which deemed most representative of the industries in the US economy. Of the 500 companies in the S&P500, 319 or 60% of the members of the index were publicly traded or consistently included in the index over the 22-year period from 1990 through 2012. Therefore, the other 181 companies were excluded from the sample so that measures of beta and returns were comparable over a consistent time frame and through the same market ups and downs.
Looking at stock price returns for the constituents of the S&P 500 relative to their respective beta over the course of 22 years reveals that there’s little to no positive correlation between a stock’s historic beta and that stock’s equity returns over the same time frame. In fact, the average correlation between stock price returns and beta is -0.07 over the 22 year history for the 319 stocks in this sample.

Figure 3: Source Bloomberg and Factset

This suggests that higher risk as measured by beta and stock price volatility does not generate better returns for investors measured over a sufficiently long period of time that is consistent with the academic literature that challenges beta as a predictive indicator of future returns. In fact, according to the empirical data, we start to see diminishing improvement in returns as beta rises to the point where not only are investors assuming greater risk without being sufficiently compensated but in fact investors are being penalized through poorer returns as beta rises. This is also consistent with Fama and
French’s conclusion that the actual CAPM line is flatter than that assumed by Markowitz and early proponents of CAPM suggesting a non-linear relationship between higher risk and higher returns.

What’s even more interesting from the empirical data is that investors can actually generate higher returns with the same level or even a lower level of stock price volatility over this same 22-year period of time that is consistent with studies around the low volatility effect.

*Figure 4: Source Bloomberg and Factset*

In the above chart, the constituents of the S&P have been sorted and ranked by highest to lowest stock price returns over 22 years. These constituents have then been grouped into 10 separate portfolios of equally weighted proportions consisting of roughly 32 companies in each portfolio. These portfolios are plotted from left to right with the portfolios on the far left representing the highest returning stocks while those on the far
right represent the lowest returning stocks. The results of this study are fascinating. The best and worst performing portfolios over the past 22 years also have the lowest and highest beta respectively over the same time frame. In fact, the best performing portfolio had an overall beta of 0.97 which is below the average beta of the market at 1.0x. In other words, investors can actually earn outsized returns while investing in stocks with lower relative beta. This supports the thesis that in fact higher risk does not generate higher relative returns that is in violation of modern portfolio theory. One of the more interesting observations from this study show that while the lowest beta portfolio clearly outperformed the S&P 500 and most other portfolios between 1990 and 2012, the best performing portfolio actually had the 5th highest beta of all of the portfolios in the sample. In addition, the portfolio with the 8th highest beta of the 10 portfolios had the 3rd best returns over 22 years. This seems to suggest that while low beta investment
strategies do generally outperform higher beta investment strategies, extremely high beta portfolios actually do relatively well over a long period of time. This suggests that while investors clearly gravitate towards companies with very low beta, they conversely also seem to gravitate towards companies with very high beta simultaneously. This may be evidence of what’s known as the longshot favorite and opposite longshot favorite bias in motion at the same time. This phenomenon will be discussed later in this paper.

In 2011, Andrea Frazzi and Lasse H. Pederson conducted one of the more interesting studies surrounding the relationship between beta and stock price returns. Their study incorporated an investment model that looked at strategies that leverage and purchase low beta stocks while simultaneously short selling high beta stocks over a period of 83 years between 1927 and 2009 for US equities.
In 58 of those 83 years, 70% of the time, their strategy delivered positive returns.

Frazzini and Pedersen also looked at International Equities over a period of 22 years between 1987 and 2009. In 16 of those 22 years, 72% of the time, their strategy delivered positive returns, 2 of those 22 years produced flat returns and 4 of the 22 years produced negative returns. Interestingly their study extended beyond equities into US treasury bonds, US credit indices and US corporate bonds. In each of these cases, their strategy of purchasing low beta securities while short selling high beta securities led to an outperformance 80% of the time, 81% of the time and 65% of the time respectively.
They concluded that stocks with high beta have been found to deliver low risk-adjusted returns versus stocks with low beta. (Pedersen, Frazzini, Lasse 40) This clearly challenged the basic premise of the capital asset pricing model in that all agents invest in the portfolio with the highest expected return per unit of risk.

The academic research alongside empirical data suggests that beta may not be a good measure of risk in gauging stocks and stock returns. There are some embedded problems with beta as a determination of the risk of an investment. First of all, beta is calculated using regression models over a historical time period. This implicitly means beta is backward looking and history may not always be an accurate predictor of the future. In addition, beta doesn’t account for changes that are in the works such as a new line of business, divestment of a business or businesses or industry shifts such as consolidation or fragmentation. Finally, beta only measures overall volatility relative to the market rather than a specific direction. For example, in an upward trending market, a stock that is outperforming the whole market will have a beta greater than 1. In this case, a stock is considered higher risk but in fact could simply be a function of strong overall fundamentals. Therefore, it may be necessary to find an alternative measure of risk when assessing the low volatility anomaly.
FINDING OTHER MEASUREMENTS FOR STOCK RISK

From our analysis of beta versus stock price returns, we can conclude that beta has little to no relationship to long term stock price returns and therefore assuming higher risk by investing in high beta stocks does not lead to above average returns over the long term. In fact, we can argue that beta may not be a good measurement for risk and return for stocks at all. Therefore, in order to understand why portfolios consisting of low volatility stocks outperform portfolios consisting of high volatility stocks, we need to find and understand where sources of risk and volatility come from. According to standard asset pricing models, the intrinsic value of a stock is equal to the present value of rationally expected real cash flows discounted by a fairly constant real discount rate. Therefore, the price of stock is a function of two major inputs namely fundamental inputs such as revenues, earnings and cash flows and more “psychological” inputs such as discount rates which are implicitly expressed through price to earnings ratios, dividend yields, price to cash flow ratios and market value to book value ratios that are collectively decided by stock market investors. Fluctuations in fundamental inputs are based on expectations of the performance of a particular company that is dependent on factors such as a company’s market share, industry growth prospects, trends in profitability, trends in the company’s cost structure, etc. In some cases such as operational expenses, corporate
strategy, investment in research & development and capital expenditures on new plant and equipment, these factors lie within the control of the management team of that corporation to manage and therefore investors place their faith and confidence in the ability of a company and its management to show consistent trends in revenues and earnings into the future. Importantly, professional industry analysts employed by wall-street investment banks and independent research firms that tend to be closely followed by individual investors and professional money managers generally establish projections and expectations of a company’s earnings prospects. There is considerable evidence to suggest that analyst forecasts and recommendations have a meaningful impact on stock prices. According to Kent Womack, an analysis of new buy and sell recommendations of stocks by security analysts at major US brokerage firms shows significant, systematic discrepancies between pre-recommendation prices and eventual values. According to Womack’s empirical evidence, for buy recommendations the average price increase after the recommendation is made is +2.4% while for sell recommendations, the average stock price decline after recommendation is -9.1%. (Womack 30) In a separate study conducted in 2001 by Brad Barber, Reuven Lehavy, Maureen McNichols and Brett Trueman using stock prices from 1986 to 1996, concluded that an investor with a portfolio of stocks with the most favorable consensus analyst recommendations would have generated an average annual abnormal gross return of +4.13% after controlling for market risk, corporation size, book-to-market multiples and price momentum effects. In fact, holding a portfolio of least favorable consensus analyst recommendations over that same time period would have returned an average of -4.91%. Stocks tend to
underperform after analysts revise down their earnings forecasts or downgrade their recommendation on a stock while stock exhibit strong positive abnormal returns after analysts revise their forecasts favorably or raise their recommendation on a stock. (Barber, Lehavy, McNichols, Trueman 32) Therefore, investors and professional money managers tend to rely heavily on industry analysts’ projections and opinions when they value, buy and sell a stock.

Fluctuations in “psychological” factors are much more difficult to predict and in many cases tend to rely on factors that are outside of a corporation’s control and outside the control of professional industry analysts. These factors include external macro variables such as rates of inflation, risk free rates of return and perceptions of a company’s future prospects, the stage of the business cycle, etc all of which can impact investor perception and aversion or attraction to risk. These psychological factors are reflected in a company’s price ratios namely dividend yield, price to earnings, price to sales, price to book value ratio etc. For example, if we look at a hypothetical example with two companies expected to generate a similar level of earnings per share of $1.00. If, for example, company A displays promising future growth prospects, high levels of profitability, dominant market share in its industry and has delivered consistent revenue growth for a long period of time, Company A may be rewarded with a higher price to earnings ratio of perhaps 15.0x. This implies that company A should trade at a stock price of $15 (15 x $1.00 per share). If, in contrast, company B’s prospects prove to be more cyclical and therefore less stable in an industry with low growth prospects, heavy
competition and low levels of profitability, investors may only place a price to earnings ratio of say 10.0x on Company B’s stock price implying a price of $10 per share. Therefore, despite similar levels of earnings, company A’s stock price and future earnings will trade at a 33% higher premium to company B simply because investors perceive company A’s earnings to be more predictable and therefore more valuable than that of company B’s earnings. Importantly, these multiples are based solely on investor perception of value. This higher valuation in Company A’s stock price is reflective of a lower equity risk premium imposed by investors relative to that of Company B’s stock price. In this example, if Company A’s stock price trades at 15.0x its earnings, that implies a 7% earnings yield (1/15) versus Company B’s earnings yield of 10%. Therefore, investors place a 300 basis point greater discount on Company B’s earnings due to their lack of confidence in Company B’s prospects relative to Company A.

Fluctuations in stock price multiples can have a significant impact on stock prices. In fact, Robert Shiller’s work in 1981 on stock price volatility versus cash flow volatility suggests that most of a company’s stock price fluctuation can be explained through fluctuations in a company’s discount rate or implied equity risk premium rather than volatility in underlying cash flows and dividends. According to Shiller, measures of stock price volatility over the past century appear to be far too high – five to thirteen times too high – to be attributed to new information about future real dividends. In fact, the standard deviation of annual changes in real stock prices is over five times higher than the observed variability in real dividends. Shiller goes on to say that these
movements in stock prices may be a function of changes in investor uncertainty with respect to a company’s dividend distribution or dividend growth path or both (Shiller 24).

Therefore, the two major sources of volatility in stock price movements comes from changes in investor’s perception about a company’s future prospects and confidence in those prospects as well as fundamental changes in professional analysts’ forecasts about a company’s earnings and future earnings prospects. Importantly, changes in investor perceptions and confidence have more influence over a stock price than changes in analyst forecasts but both are significant factors in producing stock price volatility. Hence, in order to properly understand why low volatility portfolios outperform high volatility portfolios, we need to understand what influences investor expectations in addition to factors that can influence analysts’ forecasts about a company’s prospects.

One explanation for how analysts and investors can misperceive a company’s future prospects lies in the underlying fundamental factors that make up individual companies namely leverage and profitability. In other words, companies with high leverage and low levels of profitability will tend to see greater variability in earnings and cash flows in weaker economic times relative to companies with low levels of leverage and high levels of profitability. This is because small changes in revenues for companies highly levered and operating on thin margins can have much larger impacts on earnings and cash flows versus companies with low leverage and high margins. For example, imagine two difference companies, Company A and Company B, in the same industry
with the same corporate tax rate and revenue prospects. Company A has $100 in revenues, $50 in fixed expenses and no interest expenses. Company B has the same $100 in revenues, $70 in fixed expenses and $10 in interest expenses. Therefore, Company A generates 50% pre-tax margins while Company B generates 20% pre-tax margins. If revenues across the industry fall by 10%, both companies will see their revenues decline from $100 to $90. In the case of Company A, its pre-tax margins will fall from 50% to 40% or a decline of 20% in terms of total pre-tax profit from $50 to $40. In the case of Company B, its pre-tax margins will fall from 20% to 10% or a decline of 50% in terms of total pre-tax profit from $20 to $10. Thus, Company B will be deemed to have more earnings and cash flow volatility relative to a change in revenues versus Company A.

These differences in fundamental factors were explored in depth in a study conducted by Chuck Joyce and Kimball Mayer at GMO LLC. The two analysts concluded that risk is a multifaceted concept and that it is foolish to try to reduce it to a single figure like beta. In fact, according to their work, low risk stocks are characterized by more fundamental factors such as low levels of corporate leverage, high levels of profitability, low levels of profit volatility and low relative beta. These types of companies are generally considered higher quality due to their respective fundamental attributes. In looking at both US Large Cap companies from 1965 to 2011 in addition to International equities using the standard Morgan Stanley EAFE index (EAFE: Europe, Australia, Asia and the Far East) from 1985 to 2011, Joyce and Mayer found that low risk stock high quality stocks overwhelming outperform high-risk low quality stocks in both the US and International markets (Mayer, Kimball 7)
One of the more interesting pieces of evidence for high quality low beta stocks outperforming low quality high beta stocks is in looking at the equity returns generated by Berkshire Hathaway run by the legendary equity investor Warren Buffett. Andrea Frazzini, David Kabiller and Lasse H. Pedersen looked at Warren Buffett’s alpha generation over a 30-year period in order to understand where his outsized returns came from. In finance, alpha is defined as the abnormal rate of return on a security or portfolio in excess of what would be predicted by an equilibrium model like the capital asset pricing model. In other words, the excess returns from an investment relative to the risks from that investment. Frazzini, Kabiller and Pedersen identified several unique features consistent with Warren Buffett’s portfolio one of which included buying stocks that are safe (low beta and low volatility) and high quality meaning stocks that are profitable, stable, growing and with high payout ratios. Between 1976 and 2011, Berkshire Hathaway
Hathaway’s publicly listed stock portfolio produced excess returns of 9.7% per year versus the overall stock market returns of 6.1% per year while assuming an average beta of 0.77x versus the market beta of 1.0x. (Frazzini, Kabiller, Pedersen 40) In fact, in the Berkshire Hathaway 1989 annual report, Warrant Buffett says, “It’s far better to buy a wonderful company at a fair price than a fair company at a wonderful price.” In Buffett’s own words, his strategy as a stock picker has always been to focus on high quality companies rather than trying to find bargains with low quality companies.

In looking at similar fundamental factors for companies across the 10 portfolios in this study we can find similar conclusions with respect to stock price returns, beta and average levels of corporate leverage and return on common shareholders’ equity. The table above looks at the same 10 portfolios that we constructed by looking at the S&P 500 Index for the past 22 years. In addition to beta and returns, this analysis includes 22-year average debt to capital ratios and the average return on common equity across the portfolio based on the constituents of each portfolio and the average price to earnings ratio across all stocks within each portfolio. I chose to focus on debt to capital and return on equity (ROE) because corporate leverage is an attribute closely watched by equity and fixed income investors as a gauge of bankruptcy risk and the ability for a corporate to meet its debt obligations while ROE is a broad measure of a corporation’s profitability relative to a company’s equity capital. Using the Dupont ratio, a company’s ROE is calculated by multiplying that company’s operating margin by its asset turnover by its leverage ratio. A company’s return on equity is a commonly used benchmark by
investors and corporate executive in determining how well a company utilizes its total available capital and the profitability of that company’s capital base. In this case, operating margins are defined as a company’s total revenues less total cost of good plus overhead operating expenses. Debt to capital is a commonly used measure by equities analysts in analyzing the level of indebtedness a corporation has relative to the total assets of the company. Importantly, for this analysis, only long term debt and obligations are included as opposed to short-term debt that is usually used for working capital or accounts payables. Most short-term liabilities are funded by short-term assets and therefore do not represent interest expenses or long term claims against a company’s assets.

The most interesting observation in this study is the relationship between portfolio performance, average debt to capital ratios and average ROE. The average debt to capital for the worst performing portfolio is nearly 9 times higher than the average debt to capital for the top-performing portfolio. In fact, the average debt to capital for the top 5 performing portfolios in the group was 35% vs. 46% for the bottom 5 performing portfolios in the group. In addition, the average ROE for the top five best performing portfolios was 22.9% vs. 8.9% for the five worst performing portfolios showing much higher returns on equity capital for the top performing portfolios relative to the five worst performing portfolios. In fact, the top performing portfolio generated an average ROE of 38.6% and returns of 45% over the 22 year period while the portfolio with the lowest ROE at 1.1% generated returns of just 14% over the same time period. Therefore, there
does seem to be a strong relationship between long term shareholder returns and fundamental factors such as debt/capital and return on equity capital. In fact, the average compound annual growth rate for the best performing portfolio in the group was 382% over 22 years versus flat for the worst performing portfolio. In addition, the average compound annual growth rate for the top five best performing portfolios is 117% over a 22 year period versus just 9.2% for the five worst performing portfolios.

What’s most interesting in looking at earnings per share is the standard deviation of earnings relative to their respective growth rates. While the top five best performing portfolios grew at a compound annual growth rate that was five times faster than the five worst performing portfolios, the standard deviation of earnings for the top five best performing portfolios was half that of the five worst performing portfolios. In other words, not only did the five worst performing portfolios show a lower rate of compound earnings growth over the past 20 years but the volatility of those earnings were nearly 50% greater than the top five best performing portfolios. Companies with high levels of earnings and cash flow volatility tend to be harder to predict by both analysts and investors.

In fact in looking at risk adjusted returns across the 319 stocks from our Standard & Poor’s 500 Index sample from 1990 to 2012 by ranking returns by beta alone, the highest beta portfolio would have generated an average annual return of 22.1% at an average beta of 2.25 times. In other words, the highest beta portfolio generated
approximately 10% return for every 1.0 unit of beta assumed. The second highest beta portfolio would have returned an average 30.6% for a beta of 1.68 or nearly 18% return for every 1.0 unit of beta. The third highest beta portfolio would have returned 81.9% for a beta of 1.46 or 56% return for every 1.0 unit of beta. In fact, the 5\textsuperscript{th} lowest beta portfolio generated a return of 122.7% for a beta of 1.01 or 120% return for every unit of beta. The standout risk adjusted return portfolio is actually the lowest beta portfolio with a 22 year compound average annual return of 79.5% for 0.34x beta or 232% return for every unit of beta. In other words, in general an investor could have assumed lower average beta versus the market with higher returns especially when adjusted for the level of risk assumed.

If we then rank our universe of stocks based on fundamental factors such as lowest to highest debt to total capital and highest ROEs, we get a strikingly different picture. Under this analysis, the lowest debt to capital portfolio generated a total return of 87.1% between 1990 and 2012 with an overall leverage ratio of 8.5%.
The second lowest leverage portfolio generated a return of 82.2% (portfolio 2) with a total overall leverage ratio of 19.1%. Interestingly, these two portfolios had an average beta of 0.97 and 1.29 respectively which is very basically on par with the average beta of the S&P 500 over the same time frame. In other words, higher returns versus the market without assuming much greater risk. In contrast, the second and third highest levered portfolios generated returns of 29.5% (portfolio 9) and 27.2% (portfolio 8) respectively. In fact, the top five least levered portfolios generated an average return of 81.9% versus 45.1% for the top five highest levered portfolios.
In looking at returns on equity as an additional fundamental factor, the top two portfolios with the highest average return on equity generated returns of 38.7% and 69.9% respectively while those portfolios with the lowest returns on equity generated returns of 34.7, 42.1% and 13.2% respectively. Here again we see a positive relationship between profitability as measured by ROE and returns although the portfolio with the highest level of profitability does not necessarily generate the best returns over the 22-year period, the remaining nine portfolios show a strong positive correlation between ROE and returns.

The point here is that fundamental factors such as leverage and ROE in combination tend to be better predictors of future returns vis-à-vis beta.

The analysis above seems to suggest that there’s a direct relationship between debt/capital and ROE relative to overall stock price returns. In general, companies with
lower levels of debt/capital and higher ROEs tend to perform better over time than companies with high levels of debt/capital and low ROEs. Therefore, fundamental factors such as leverage and return on equity appear to be better measures of risk and therefore better predictors of future stock price returns versus a single variable such as beta and standard deviation. While beta does a good job in assessing day to day stock price volatility, in general beta does a poor job in forecasting future stock price returns. This makes sense from a business perspective. ROE and debt/capital measure a company’s fundamental characteristics. In looking at different companies across different industries, we tend to find that over the long term, most companies have a difficult time generating abnormally high returns on capital far and above their cost of capital for a sustainable period of time. That’s because abnormally high levels of return tend to entice competition to enter a market and try to compete for a slice of these high returns. Higher competition means that returns for a company’s product or service is likely to erode until returns stabilize to a more normal level generally commensurate with that company’s or that industry’s cost of capital. Returns on capital generally don’t fall below the cost of capital because companies would choose to shut their operations if returns on capital fell below the cost of capital. Why stay in business if you’re bound to generate economic losses? Therefore, companies that generate high ROEs over a long term time horizon tend to be in industries with very little competition and therefore companies have oligopolistic or monopolistic positions or companies have a technological advantage or brand equity that is difficult for competition to replicate and compete away or a combination of both. Either way, we see that companies with high
ROEs tend to have abnormally unique characteristics and fundamental factors which also tend to insulate them through the ups and downs of economic cycles. In addition, debt/capital tends to measure a company’s total leverage which can be a good attribute in goods economic times and a highly negative attribute during bad economic times. Excess leverage can have a number of deleterious impacts on a company. Excess leverage can restrict a company’s ability to invest and expand in growth projects if debt payments consume a large portion of a company’s cash flow. This can lead to reduced market share and limit a company’s ability to successfully compete against its peers. Similarly, high levels of leverage can psychologically impair a management’s willingness to take risks in developing new products or going after new markets. With an excessively conservative management team companies can become inflexible and lose competitiveness over time. Finally, excess leverage can amplify cash flow volatility especially during a bad business cycle or economic cycle. In addition, if a company’s cash flows and balance sheet come under question, creditors may demand a higher rate of interest. Therefore, high leverage and high debt payments can actually create a vicious cycle of deteriorating cash flow volatility led by high debt creating more cash flow volatility as interest rates on that debt move higher.
THE ROLE OF ANALYSTS FORECASTS IN STOCK PRICE VOLATILITY

Stock market valuation only explains part of the low volatility anomaly. As discussed earlier, stock prices are a function of both multiples placed on earnings by investors as well as projected fundamental prospects such as revenues, earnings and cash flows set by professional industry analysts. Academic research has proven that individual traders and professional money managers with respect to how a company’s stock price is perceived by the broader market closely follow professional analysts’ projections, opinions and recommendations about stocks. In order to understand the low volatility anomaly, we need to understand the role that a company’s fundamentals including revenues, earnings and cash flow plays in impacting analyst’s projections about its future prospects. More specifically, we need to understand how accurate analysts are in projecting earnings and cash flows for publicly traded companies, what impacts and influences these projections and most importantly how earnings predictability impacts stock market valuations. Ilia D. Dichev and Vicki Wei Tang conducted one of the more interesting studies on this subject. Dichev and Tang looked at a sample of 22,113 publicly traded companies and their earnings and operating cash flows between 1984 and 2004. The study looked at cash flow volatility over the 20 year time period. Companies were then separated into quintiles based on their level of cash flow volatility. Those with
the highest volatility were placed into the highest quintile while those with the lowest volatility were placed into the lowest quintile. In addition, Dichev and Tang looked at Wall Street analyst’s earnings and cash flow forecasts on both short term and long term time horizons. The two authors make a number of important conclusions. First, short term specifications indicate that low-volatility earnings have much higher persistence as compared to high-volatility earnings. Beyond short-term specifications, long-run tests indicated that earnings volatility has substantial predictive power for up to 5 years in the future. Earnings with low volatility have remarkably high persistence and correlation during the entire predictive horizon, while earnings with high volatility show quick reversion to the mean and little reliable predictability (Dichev, Tang, Wei 21). This means that companies that have low earnings and cash flow volatility in the short term tend to show a persistently low level of future earnings volatility. This future level of earnings persistence is even stronger when companies show low volatility over a longer-term time horizon. Thus, if a company shows low cash flow volatility over a 1-year and 5-year time horizon, there’s a strong likelihood that the same company will show low cash flow volatility and therefore higher cash flow predictability into the future. On the other hand, companies with high cash flow volatility are more likely to see their earnings and cash flows mean revert to an average level over the long term and therefore show more volatility in the short term. Therefore, earnings volatility is inversely related to earnings predictability.
The second important conclusion from Dichev and Tang’s study was that companies with higher earnings volatility also tend to have larger errors in analyst’s forecasts over a given period of time than those of companies with low earnings volatility. These errors tend to be larger and more frequent the longer the time horizon of the study. Based on empirical results, their study found that it is easier to predict earnings 5 years ahead for low-volatility firms than to predict earnings 1 year ahead for high volatility or even all firms. This suggests earnings volatility has a remarkable differentiating power in the long-run prediction of earnings. In fact, based on their research, the two authors found that on average analysts do not fully understand the implications of earnings volatility for future earnings and in quantitative terms analysts impound less than half of the full implications of earning volatility for earnings predictability. Additional tests revealed that the results are nearly the same for 2-year-ahead earnings forecasts (Dichev, Tang, Wei 21).

In looking at our sample of 319 stocks from the S&P 500 between 1990 and 2012, it’s very clear that companies with the fewest negative earnings surprises over the course of the past 22 years outperformed those companies with the most negative earnings surprises. For this study, a positive or negative earnings surprise is defined as differences between analysts’ estimates for a company’s earnings on January 1st of each calendar year and the actual company’s earnings report on December 31st of that same calendar year. Clearly and unsurprisingly, we can see from figure 11 that companies that tend to exceed analyst’s forecasts tend to perform better than companies that disappoint analyst
estimates. Figure 11 looks at a company’s actual earnings in a given year relative to analyst forecasts at the beginning of that year and the number of years between 1990 and 2012 when a company positively or negatively surprised analyst forecasts. In fact, the highest returning portfolio between 1990 and 2012, on average, exceeded analyst consensus forecasts 69% of the time while the worst performing portfolio negatively surprised analyst consensus expectations 57% of the time over the same 22 year period.

**Figure 10: Source Factset**

Additionally, Figure 12 further supports the idea that companies with higher quality fundamentals tend to have more stable earnings predictability and tend to generate better returns for investors over the long run. Figure 12 shows us the relationship between companies that most frequently report negative year-over-year earnings declines and their respect leverage ratios (defined here as debt-to-capital) and operating margins. I’ve used operating margins in place of ROE in this case as operating margins are a more direct measure of year-to-year change in business conditions while ROE has multiple factors
namely leverage, asset turnover, operating margins and tax rates. Again, we can see that in general, companies with lower leverage and higher operating margins tend to have fewer years with earnings declines and generally outperform over the long run. In fact, the portfolio with the lowest debt to capital also had the fewest years with negative year-over-year earnings declines. This is most likely due to the fact that companies with high leverage and low profitability have much higher levels of operational and financial gearing through up and down economic cycles. In extending this study beyond just positive and negative earnings surprises, we ranked the 10 portfolios based on companies that reported the smallest deviation between estimated earnings forecasts and actual earnings reports regardless of the whether the actual report was better or worse than projected. In Figure 12, we can see, interestingly, that those companies that had the smallest deviation between estimated earnings and actual reported earnings generally had much lower beta than companies with large deviations from estimated versus actual earnings. In addition, companies with the lowest deviation from estimates also generally had much higher operating margins. This supports the idea that stocks with high volatility generally have less earnings predictability and that earnings predictability is partially of a function of fundamental factors such as profitability. This may be due to the fact that companies with higher average levels of profitability and therefore generate higher average returns on capital are generally companies with high and sustainable market share in industries with stable and predictable end market demand. These types of companies will have more stable earnings over the course of different economic cycles. Overall, Figures 11 and 12 show us that analysts have a harder time predicting
future earnings for companies with high levels of leverage and low levels of operating margins and that consequently these same companies tend to show higher levels of volatility over a long term time horizon due to this lack of earnings predictability, higher frequency of earnings declines and generally higher perceived level of uncertainty and risk.

Figure 11: Source Factset and Bloomberg
Figure 12: Source Factset
BEHAVIORAL EXPLANATIONS FOR THE LOW VOLATILITY ANOMALY

There are a number of theories using behavioral economics as a basic framework to attempt to explain this low volatility anomaly in stock market returns as it relates to investor behavior. Malcolm Baker, Brendan Bradley and Jeffrey Wurgler suggested that such behavior is reflective of investor preferences for lotteries, representativeness and overconfidence as three reasons based on behavioral economics to explain the low risk anomaly (Baker, Bradley, Wurgler 26). Many of these findings are grounded in research first published by Nobel Prize winning psychologists Daniel Kahneman and Amos Tversky in the late 1970s and more recent work conducted by Richard Thaler of the University of Chicago. Preference for lotteries suggests that when presented with an opportunity to win a large expected payoff combined with the prospects of a limited but negative expected payout investors will choose to take the gamble. In other words, if given a 50% chance of losing $100 versus a 50% chance of winning $110, most people will choose not to gamble despite a positive expected payoff of $5 given the potential large loss of $100. This is because of two concepts called Loss Aversion and Prospect Theory, first defined by Kahneman and Tversky in 1979. According to Kahneman and Tversky, loss aversion suggests that investors would shy away from volatility for fear of realizing a loss. A gambler’s risk aversion can be defined to depend on the minimum
probability of success that would him to accept a bet. The higher the minimum probability he demands, the higher his risk aversion. Despite the idea that a rational person would take the bet given the positive expected payoff, the magnitude of negative utility from realizing a loss or the possibility of realizing a loss is much greater than the same magnitude of positive utility from realizing a gain or the possibility of realizing a gain. The notion that people derive greater negative utility from a loss relative to the positive utility they would gain from a commensurate amount of profit is central to Daniel Kahnemann’s Nobel Prizing winning work around Prospect Theory. As Kahnemann explains, for some reason outside of the bounds of rational decision-making, individuals place a greater “penalty” on the possibility of realizing negative utility versus the same value of positive utility. But suppose that same individual is given a 0.12% chance of winning $5,000 or a 99.88% chance of losing a mere $1. Again, this gamble presents an individual with the possibility of a large and positive expected payoff but with the possibility of a small but negative expected payout but in this case most people will choose the gamble despite the near certainty of realizing a loss. According to Kahneman and Tversky’s notion of Prospect Theory, this is because the magnitude of potential negative utility is small enough that the gambler can “take the pain” of a potential loss for the prospect of a large positive payoff (Kahneman, Tversky, Daniel 9). This explains the amount of money spent on roulette wheels and lotteries despite having negative expected payoffs. Carrying this illustration over to the stock market, with individually low priced highly volatile stocks, investors perceive that they have limited liability with a small chance of doubling or tripling in value in a short period of time and
therefore choose to take the risk. In short, these high volatility stocks represent lottery tickets in the mind of investors.

Another explanation cited as an explanation for the low volatility anomaly suggests representativeness. According to Kahneman and Tversky, representativeness takes place when people use preconceived biases and judgments to attach probabilities to an outcome without respect to prior probabilities. If people evaluate probability by representativeness, prior probabilities often get neglected and can lead to erroneous and serious errors based on judgments of probability rather than mathematical facts. One classic case study conducted by Kahneman and Tversky took place when subjects were shown brief personality descriptions of several individuals, allegedly sampled at random from a group of 100 professionals namely engineers and lawyers. In one experimental condition, subjects were told that the group from which the description was drawn consisted of 70 lawyers and 30 engineers and in another experiment subjects were told that the group consisted of 30 lawyers and 70 engineers. After being given a description of the individual without disclosing that person’s occupation, subjects were asked to assess the probability that the individual was an engineer or a lawyer. Despite the odds of a lawyer vs. engineer standing at 70:30 in the first experiment and 30:70 in the second experiment, the subjects produced essentially the same probability judgments evaluating the likelihood that a particular description belonged to an engineer rather than to a lawyer by the degree to which this description was representative of the two stereotypes with
little to no regard for prior probabilities given for the categories (Kahneman, Tversky, Daniel 7).

As it relates to stocks, investors tend to look at high flying stocks like Apple, Microsoft and Intel over the years and conclude that speculative high risk stocks are the best way to make large amounts of money in the stock market while ignoring the low probability with which such companies or stocks actually exhibit outsized returns over the long run. In addition, according to Kahneman and Tversky, people will often exhibit insensitivity to sample sizes when establishing judgment probabilities (Kahneman, Tversky, Daniel 27). In other words, investors look at successful stocks like Microsoft, Amazon and Apple and assume these companies are more often the rule rather than the exception to the rule. In the example of Microsoft, Amazon and Apple, despite looking at a sample size of just three, investors will tend to conclude that most technology companies are successful stocks.

Finally, the authors Baker, Bradley and Wurgler looked at investors’ overconfidence as another explanation for the low volatility phenomenon. Overconfidence suggests that investors place more confidence and therefore a higher probability on an outcome with their own judgments than actual outcomes (Baker, Bradley, Wurgler 12). According to Dale Griffin and Amos Tversky, people’s confidence is determined by the balance of arguments for and against the competing hypothesis, with insufficient regard for the weight of the evidence (Tversky, Griffin 24).
In other words, people are often more confident in their judgments than is warranted by the facts. Overconfidence is not limited to lay judgment or laboratory experiments. Dun & Bradstreet’s well-publicized observation that more than two-thirds of small businesses fail within 4 years suggest that many entrepreneurs overestimate their probability of success.

One of the more interesting examples of overconfidence involves what’s often called the Favorite Long Shot Bias. R. M. Griffith first observed the Favorite Long Shot bias in 1949. Griffith looked 519 horse races in 1947 at the spring meets of Churchill Downs, Belmont and Hialeah. Griffith used horse track races because in horse race betting, the odds on the various horses in any race are a function of the proportion of the total money that is bet on each and does therefore the house set socially determined rather than pre-established odds. On the other hand, the objective probability for winners from any group of horses is given a posteriori by the percentage of winners. Therefore, the odds express (reciprocally) a psychological probability of outcomes while the percentage winners at any odds group measures the true probability of outcomes. Griffith wanted to understand whether there were consistent and significant discrepancies between the psychological probabilities and the actual outcomes. From his findings, Griffith concluded that while most of the betting pool for horse races are placed on the short odds (the higher probability winning horse), the amount is not great enough relative to what the actual outcomes suggest. In other words, bettors consistently wagered too much on horses with long odds of winning and too little on horses with highly certain odds of
winning. This suggests that investors tend to overvalue long shot bets while undervaluing sure shot favorites. In other words, when looking at two different bets, one with large but highly unlikely payoffs or the long shot and one with smaller but more highly probable payoffs or the sure shot, investors will tend to bet more often on the long shot than the odds would suggest. More specifically, the expected returns per dollar bet increase monotonically with the probability of the horse winning. Favorites win more often than the subjective probabilities imply and long shots less often. This means that favorites are much better bets than long shots (Griffith 4). In 1986, Ziemba and Hausch published studies based on over 50,000 horse track races in the State of California. In the figure below, Ziemba and Hausch illustrates the favorite long shot bias using a simply diagram. Expected returns per dollar bet are plotted for horses at various market odds, using a transaction cost assumption of $t=15.33\%$, which applies to the State of California.

The horizontal line indicates the point at which the returns are the expected $0.8467 (1-t)$. This occurs at odds of about 9-2 (i.e. about a 15% probability of winning). For odds above 18-1, there is a steep drop in the expected return, with returns falling to only 13.7% per dollar wagered at 100-1. This means that someone were to bet on a horse with 100-1 odds, rather than winning one race in 100, that person would win only win one race in 730. For odds below 3-10, expected returns are positive with about 4-5% for the shortest-odds horses. In fact, extreme favorites, those with odds of less than 3-10 (greater than 70% chance of winning) actually have positive expected values (Ziemba, Hausch 4).

In one of the more interesting studies on this topic, Erik Snowberg and Justin Wolfers (2010) looked at 6.4 million horse race starts in the United States from 1992 to 2001.
After looking at the frequency of bets placed on horses with different odds, the authors noted a substantial favorite long shot bias. According to the authors, “using large-scale dataset we find evidence in favor of the view that misperceptions of probability drive the favorite long shot bias…” Based on their studies, the rate of return to betting on horses at long odds is much lower than the return to betting on favorites. Interestingly, their work adjusts for risk loving utility functions versus risk neutral or risk-neutral functions in keeping with their conclusions. They accomplish this by looking not only at the total amount that is placed on sure shot and long shot horses relative to their expected returns but also by segregating risk-loving bettors versus risk-neutral behavior where risk-neutrality is defined as gamblers placing bets based on odds that are misperceived relative to the actual odds offered by the horse-track. By looking at gamblers that not only over-bet long shots but also the size of their relative bets versus risk-neutral players, they can separate risk loving versus risk neutral gamblers and therefore test the model under both conditions. The utility functions for risk loving and risk neutral gamblers are then estimated from the pricing of winning bets and test for long-shot and sure-shot behavior. In their analysis, the bias for long shots versus favorite bets exists regardless of whether a gambler is risk loving or risk neutral. In addition, their results suggest that the low rates of return to betting on long-shots are rationalized by bettors who bet as though the tiny probabilities of winning actually have moderate probabilities of winning because of misperceptions of risk rather than an affinity towards taking risk. Similar to Ziemba and Hausch, the authors illustrate that the rate of return on win bets declines as risk increases suggesting that bettors overestimate the returns from horses with low odds of
winning races and that this overestimation of returns actually rises as the odds decline. Figure 13 shows this in graph format. Horses are grouped according to their odds and the rate of return to betting on every horse in each group is then calculated. The data is graphed on a log-odds scale in order to better show the relevant range of the data, hence the reason for the bulge in the graph at 10/1 odds. The average rate of return for betting favorites is -5.5% while for horses at the mid-range of 3/1 to 15/1 odds yield a rate of return of -18% while real long shots, horses at 100/1 odds or more, yield much lower returns of -61%. The expected return from rational betting behavior is shown as the dark
black line. Snowberg and Wolfers explain that if bettors were perfectly rational, then the odds of a horse winning a race would more closely approximate the expected payoffs of placing a bet. Instead, Snowberg and Wolfers found that in fact when looking at actual betting returns that bettors lose more money on long-shot horses than one would expect and generate fewer losses than one would expect on sure shot horses. What’s important about horse track racing is that it incorporates pari-mutuel betting. Pari-mutuel bets are betting systems in which all bets of a particular type are placed together in a pool and payoff odds are calculated by sharing the pool among all winning bets. In other words, the gamblers set the odds based on how heavily they bet on certain horses as opposed to the “house” or the race track in this example. As an example, if $100 of bets are placed on 3 different horses of which $50 are placed on horse 1, $30 on horse 2 and $20 on horse 3, the payoff on horse 1 would be 1:1 or $1 in returns for every $1 bet. The payoff odds on horse 2 would be roughly 3:1 or $3 in returns for every $1 bet and the payoff on horse 3 would be 5:1 or $5 in returns for every $1 bet. When looking at race day results for both standard bets and complex bets such as trifecta betting, Snowberg and Wolfers found that bettors place greater odds on long shot bets than what actually transpires on race day and similarly bettors place lower odds on sure shot bets relative to what actually transpires. In fact, because overall bets are pooled, over-betting certain odds implicitly means under-betting elsewhere with the payoff odds. In this case, under-betting takes place amongst the higher odd horses. By placing heavier bets on long shots relative to the expected payoff on the long shot horse, investors are “over-paying” for the long-shot
bet. In fact, neglecting for transaction taxes, sure shot investments would generate a slightly positive payoff (Snowberg, Wolfers, 723-746).

Richard Thaler suggests a number of factors could help explain this anomaly. First, both of these studies suggest that bettors tend to overestimate the chances that the long shot bets will win and as a result also underestimate the chances that favorite “sure shot” bets will win. The fact that positive expected returns can be made by betting on horses with higher odds and lower payoffs suggests this to be the case. In addition, bettors might overweight the small probability of winning in calculating the utility of the bet. In other words, bettors become so enthralled with the prospects of winning large payoffs that they overestimate the probability that these payoffs will happen. In addition, bettors may derive utility simply from holding a ticket on a long shot. Given the fact that placing a wage is represents a small out of pocket expense, the prospects of a large payoff outweigh the potential small losses that a bettor is likely to incur. Finally, bettors may choose a bet for very irrational reasons such as a horse’s name. Such bettors can actually drive the odds down on the worst horses, with the “smart money” simply taking the better bets on the favorites (Thaler 74).

Russell S Sobel and Matt E. Ryan offer up two interesting explanations for the existence of the long shot bias namely risk-preference theories and information-perception theories. The first group of theories attributes the long shot bias to a preference for risk among gamblers. According to Sobel and Ryan, consumers have a
globally risk-averse utility function yet over the relevant range concerning gambling and betting, the utility function becomes locally risk loving (Sobel, Ryan 371-385). Starting with conclusion that bettors are risk loving, Quandt in 1986 shows that because of the additional utility derived from taking high-risk high variance bets, the payoff of such a bet must necessarily be smaller for the high-risk long shot bet than the low-risk favorite bet. In other words, because gamblers and bettors enjoy taking risk and derive more utility as they take more risk, the payoffs from taking a high-risk bet should be lower than if gamblers were equally risk averse as the general population because of the additional unit(s) of utility a gambler receives from taking risk. The second group of theories, the information-perception theories, places the activities of the bettor as a reaction to new information at the time of betting as opposed to being naturally predisposed to taking riskier bets (Quandt 7). According to Snowberg and Wolfers (2004), studies by cognitive psychologists suggest that bettors do not perfectly absorb information and that people are systematically poor at discerning between small and tiny probabilities hence they price each similarly. Furthermore, certain events are strongly preferred to extremely likely events, leading to even very likely events to be under-priced. Ultimately, it is the representative bettor’s inability to process information correctly that leads to a favorite-long shot bias in the information-perception theories (Snowberg, Wolfers 723-746). Daniel Kahneman, in his book “Thinking, Fast and Slow” explains that all people have two systems for making a decision. System 1 operates automatically and quickly, with little or no effort and no sense of voluntary control while System 2 allocates attention to the effortful mental activities that demand it, including complex computations. The
operations of System 2 are often associated with the subjective experience of agency, choice and concentration. For example, when a person buys a lottery ticket, the thrilling possibility of winning the big prizes is shared by the community and reinforced by conversations at work and at home. Buying a ticket is immediately rewarded by pleasant fantasies in which possibility takes over from actual probability. In this example, System 1 takes over System 2 in terms of framing the decision of whether or not to buy the lottery ticket. In Kahneman’s recent research, emotion and vividness influence fluency, availability and judgments of probability accounting for our excessive response to the few rare events that we do not ignore (Kahneman 231). Benoit B Mandelbrot writes extensively about this in his book “The (Mis) Behavior of Markets. Mandelbrot points out that contrary to orthodoxy, stock price changes are very far from following the standard Gaussian bell curve. If they did, one should be able to run any market’s price records through a computer and analyze the changes and watch them fall in the approximate “normality” assumed by Louis Bachelier’s random walk. They should cluster about the mean, or average, of no change. In fact, the bell curve fits reality very poorly. According to Mandelbrot, from 1916 to 2003, the daily index movements of the Dow Jones Industrial Average do not spread out on graph paper like a simple bell curve. The far edges flare out too high: too many big changes. Theory suggests that over that time, there should be fifty-eight days when the Dow moved more than 3.4%; in fact, there were 1,001. Theory predicts six days of index swings beyond 4.5%; in fact there were 366. And index swings of more than 7% should come once every 300,000 years; in fact,
the twentieth century saw 48 such days. Therefore, according to Mandelbrot’s research, investors tend to underestimate the risks in owning stocks (Mandelbrot 123).

In contrast to the Favorite Long shot Bias, many studies suggest a bias in the other direction often referred to as the Opposite Long shot Bias. Linda and Bill Woodland conducted one of the more famous studies involving the Opposite Long shot Bias in 1994 using professional baseball statistics as their data set. The analysis included 24,603 major league baseball games for between the 1979 and 1989 seasons. Woodland and Woodland looked at the actual percentage of times the underdog team won their baseball games relative to the odds placed on that team’s chances of winning prior to the game. According to the Woodland team, using regression analysis and z-test scores, their research indicated that in contrast to racetrack betting, baseball bettors overbet the favorites rather than the underdogs. This reverse bias is even more pronounced when heavy underdogs are excluded from consideration. According to their conclusion, this long-standing preference of bettors to overbet favorite teams may represent true market inefficiency because people think that betting on the favorites shows and being perceived as more knowledgeable is more important than beating the odds (Woodland, Woodland 10). In their book “Scorecasting: The Hidden Influences Behind How Sports are Played and Games are Won,” Tobias Moskowitz and Jon Wertheim interviewed Dallas Cowboys executive Mike McCoy who was brought on by team owner Jerry Jones in 1991 to help develop a strategy for drafting a winning team. McCoy noticed that the value of football player draft picks varied dramatically relative to how high or low that player was picked
in the overall draft. A first pick in round one of the NFL draft was paid an amount equivalent to the combined value of the sixth pick and the eighth pick and more than that of the final four picks of the first round combined (Moskowitz, Wertheim 175-192). In fact two prominent behavioral economists, Richard Thaler of the University of Chicago and Cade Massey at Yale, noted that historically the number one pick in the draft is typically paid about 80% more than the eleventh pick in draft on the initial contract. Thaler and Massey found that the inflated values teams were assigning to high picks were remarkably consistent. The two economists then looked at whether these values were justified after examining post draft player performance and results. They found that higher picks are generally better than lower picks on average and the first round draft picks on average post better numbers than do second round draft picks who in turn post better stats than third round draft picks but that the stats also showed that top round draft picks’ performance weren’t that much better than second or third round draft picks relative to the salary differentials they were paid. Thaler and Massey concluded that the probability that the first player drafted at a given position is better than the second player drafted at the same position is only 53%, slightly better than a tie. The probability that the first player drafted at a position is better than the third player drafted at the same position is only 55%. The probability than the first player drafted at a position is better than the fourth player drafted is only 56%. In other words, by selecting the consensus top player at a specific position versus the consensus fourth best player at that position increases performance, measured by the number of starts, by only 6%. Yet teams will end up paying, in terms of both players and dollars, as much as four or five times more to
get that first player relative to the fourth player. In fact as a professional football team, the smart strategy may be to trade your 1st round pick for a number of 2nd and 3rd round picks despite getting plenty of flak from your fans (Thaler, Massey 35).

**Figure 14**

![A hypothetical value function](image)
COEXISTENCE OF THE FAVORITE & OPPOSITE FAVORITE LONGSHOT BIAS

Based on the academic research and the empirical data collected between 1990 and 2011, there seems to be evidence to indicate that the stock market displays similar characteristics to prospect theory and the notion of loss aversion and that as a result, there exists both a favorite long shot bias and an opposite favorite long shot bias in stock markets. As discussed earlier, prospect theory suggests that investors perceive a higher level of negative utility from a given loss versus the positive utility from an equivalent level of gain as show by the equation \([+U] < [U^-]\). For our study, we’ll assume that \(U\) is equivalent to a unit of earnings power from a company. As a result, investors will place a greater value on avoiding \(U^-\) by assigning a higher value to \(U^+\). This is natural as companies perceived to have safer and more predictable earnings power get rewarded through higher long term equity returns rather than companies perceived to have less predictable “less safe” earnings power. This is based on the assumption that most individual investors and asset managers are generally risk averse.
How can we tie this idea of predictable earnings power back to the low volatility anomaly? Behavioral studies suggest that investors are overconfident in their ability to judge an outcome. Just as subjects in an experimental setting use representativeness and ignore given probabilities when asked about whether a description fits a lawyer or a doctor, investors will overestimate their confidence in the future prospects for a company when those expectations are based on their own research, whether they use a company’s products and services or whether that stock is held in their own portfolios. If an investor’s family uses Apple Computer products at home, that investor may place greater confidence in Apple’s future prospects based on a very small sample size. In addition, empirical studies suggest that earnings volatility can have a significant impact on stock market valuation that is ultimately a reflection of investor confidence.

This overconfidence gets reflected in higher stock price multiples for companies with lower volatility and higher earnings predictability. In 2005, Graham et al surveyed 401 financial executives to determine the key factors that drive decisions related to reported earnings and found a pronounced aversion to earnings volatility. In fact, 97% of respondents express a preference for smooth earnings. In exploring the reasons for this finding, 80% of the respondents stated that their aversion to volatility was due to their belief that higher earnings volatility reduced future earnings predictability (Graham 3-73). According to a separate study conducted by Ronnie Barnes in 2001 after adjusting for firm size, balance sheet leverage, current levels of profitability and the level of current
investment and sales growth, there is a significantly negative relationship between the market to book ratio and earnings volatility (defined as the coefficient of variation of various earnings measures). This is consistent with the idea that less variance in earnings should be desirable if one wants or needs more of a sure thing. In addition, Barnes found a statistically significant relationship between firms in the 1st and 99th percentiles of earnings volatility and their respect market to book value ratios. On average, Barnes found that there is a 0.04 difference in market to book value ratios between a firm whose earnings volatility is in the 5th percentile and one in the 95th percentile while there is a 0.23 different in market to book value ratios (approximately 15% of the median) between firms in the 1st and 99th percentiles (Barnes 1-47).

This suggests that part of the low volatility anomaly can be explained by investors’ aversion to earnings volatility, similar to Kahneman and Tversky’s work around Prospect Theory. Investors perceive earnings volatility similarly to how they perceive the potential of realizing a loss on a gamble. Given that investors realize greater negative utility from a given loss relative to the positive utility they realize from a given profit of a similar magnitude, investors will place a premium on stocks with lower chances of losing money relative to stocks with a higher chance of losing money. As a result, stocks with lower earnings volatility can command a higher valuation by the stock market and therefore outperform stocks with a similar level of earnings but with higher earnings volatility. This may actually support the idea that the favorite long-shot bias and the opposite favorite long shot bias existing and occurring at the same time. Importantly, this
study also provides evidence supporting the notion of the favorite and opposite favorite long shot bias in stock market. The empirical data used in this study showed that over the past 22 years portfolios consisting of those companies with high quality fundamentals measured by balance sheet leverage, returns on capital and consistent earnings performance relative to analyst expectations generally outperformed portfolios consisting of companies with lower quality fundamentals within the ten portfolios actually showed some of the weakest performance in terms of stock price performance over the past 22 years. Interestingly, the two portfolios with the best and worst fundamentals respectively measured by leverage and ROE actually showed relative poor performance versus the 10 portfolios in aggregate. Figure 15 looks at return on equity in 1990 for the 325 companies that make-up the 10 portfolios in our sample and their respective returns between 1990 and 2012. The portfolio consisting of those companies with the highest ROEs and the portfolio consisting of those companies with the lowest ROEs ratios generated 45.0% and 16.4% respectively while the 10 portfolios in aggregate generated returns of 48.2% over the same time period.
Figure 16 looks at debt/capital ratios for those same companies across the 10 portfolios in our sample. The portfolio consisting of those companies with the lowest and highest debt/capital ratios generated 38.7% and 13.2% returns respectively over the 22 years between 1990 and 2012, again below the average 48.2% for all ten portfolios during the same time frame.
The point here is that had an investor simply invested his or her money in those stocks with the best fundamentals or the worst fundamentals in an attempt to generate outsized returns, that investor would have underperformed the broader stock market. In order to understand why, we need to look at the relative value placed upon companies with the best and worst fundamentals across long term time horizons. Figures 17 and 18 look at the average price-to-earnings ratios (P/E) for our sample portfolios sorted by lowest to highest debt/capital ratios and highest to lowest returns on equity. As discussed earlier, P/E ratios are essentially qualitative values determined by market participants and placed on stocks to determine a companies’ stock price. Recall, a stock’s price is equivalent to a companies’ earnings per share (EPS) multiplied by its P/E ratio. The figures below suggest that companies with the lowest debt/capital ratio and the highest debt/capital ratio trade at relatively high P/E ratios versus the 10 portfolios in aggregate. The portfolio consisting of those companies with the lowest debt/capital ratio traded at an average P/E
of 22x between 1990 and 2012 versus the average P/E ratio of 20x over the same time frame for all 10 portfolios, a premium of 10% over the group average. Similarly, the portfolio consisting of those companies with the highest debt/capital ratio traded at an average P/E of 21.3x over the same time frame, a premium of 7% over the group average.

In other words, investors pay a high premium for companies with the best and worst debt/capital ratios. In addition, figure 20 shows a similar analysis except looking at ROE instead of debt/capital. Again, the portfolios of companies with the highest and lowest ROE ratios over the past 22 years traded at an average P/E of 25.5x and 21.3x reflecting a premium of 28% and 7% respectively.

Figure 17: Source Factset
While it may seem obvious that stocks with the best fundamentals would command a higher premium versus those stocks with worse fundamentals, it seems counterintuitive that stocks with the absolute worst fundamentals can actually trade at relatively high valuations. This is mostly driven by expectations for earnings recovery and the value investor mind-sight, sometimes referred to as contrarian investing. Value investors often invest in companies with poor prospects that are generally out-of-favor and “un-loved” by the crowd in hopes of a company’s fundamentals improving over time. These contrarian investors can be analogous to long shot horseracing bettors placing bets on horses with the lowest odds but highest payoffs. Thus, stocks with the worst fundamental attributes actually command high valuations because investors perceive large potential returns contingent upon an improvement in fundamentals.
Our analysis of P/E ratios over the 22 year time frame between 1990 and 2012 relative to performance, debt/capital ratios and ROEs suggests that investors actually seem to perform poorly when investing in companies with extremely strong and extremely poor underlying fundamentals. In other words, investors tend to over-bet companies with the best fundamentals or the “sure-shots” and the worst fundamentals or the “long-shots” simultaneously to the point where stocks in both “tails” generated the lowest overall returns relative to stocks in the middle of the pack.

In a related study titled “Do Financial Markets Reward Buying or Selling Insurance and Lottery Ticket?” Antti Ilmanen, managing director at AQR Capital Management LLP suggested that selling financial investments with insurance or lottery characteristics should earn positive long-term premiums if investors tend to overpay for these characteristics. His premise was that all else being equal, investors prefer assets that tend to generate positive absolute returns during volatile markets and thus make their portfolios more positively skewed, in other words positive relative returns vis-à-vis the market with similar or lower levels of volatility. Yet, since these assets are scarce, investors will tend to pay a high price for this characteristic. Conversely, because investors dislike negative skewness, in other words negative returns vis-à-vis the market with similar or higher levels of volatility, they’ll require an extra reward or required risk premium in order to hold such an asset. In this case, investors will tend to overly punish or undervalue an asset relative to its true intrinsic value. Ilmanen goes on further to
suggest that investors have nonstandard preferences in that small chances of very large
gains with almost certain but small expected losses can induce risk seeking while
investors become risk averse when a gamble involves small chance large impact losses
with almost certain small expected gains so much so that they pay for insurance to avoid
such losses. Citing work by Bordalo, Gennaioli and Shleifer (2010), Ilmanen suggests
that decision makers overweight the likelihood of salient states in which lotteries and
insurance payouts have extreme, contrasting payoffs. He concludes, based on his own
empirical research, that strategies that sell assets with insurance and lottery ticket like
characteristics have delivered positive long-run rewards in a wide range of investment
contexts. Conversely, buying financial catastrophe insurance and holding speculative
lottery-like investments have delivered poor long-run rewards (Ilmanen 9).

We can draw a similar analogy to stocks in the S&P500. Over the 22 years from
1990 to 2012, investors were poorly paid relative to the market by investing in safe
companies with near “bullet-proof” fundamentals and companies with extremely weak
fundamentals. This is because investors tend to be both risk averse and risk seeking in
terms of how they perceive certain stocks. Companies with high profitability and pristine
balance sheets are viewed insurance protection and vehicles for capital preservation.
Since these companies are few and rare, they tend to be over-valued as investors herd into
their stocks. Similarly, companies with low levels of profitability and weak balance
sheets are viewed as lottery tickets with potential for very large gains when the market is
trending up. Therefore, the stocks of companies exhibiting these characteristics will tend
to become overvalued especially in a portfolio where investors can limit losses by taking small positions similar to the payoff profiles of a lottery ticket. In fact, Ilmanen goes further and suggests that given most investors have constraints and limits on how much leverage they can assume behind an investment, investors will tend to use stocks with lottery ticket like characteristics as a means of enhancing returns without the use of leverage (Ilmanen 9).
It is important to understand the critical arguments against behavioral economics. Most importantly, behavioral economists challenge the main tenet of Rational Choice theory namely that collectively, individuals will act rationally in terms of the decisions they make based on the information they’ve been given with regard to choices at hand. According to Mark Kelmon at Stanford University, rational choice theorists counter with four main arguments vis-à-vis behavioral economists. First, rational choice theorists claim that critics often misinterpret the ends that subjects in fact are seeking by “observing” that they have failed to meet these ends. In other words, if a subject makes a decision that seems irrational based on what we believe that subjects intent to have been, in fact from the perspective of that subject his or ends may seem perfectly rational. Second, rational choice theorists argue that while it may appear that agents are acting irrationally, they are in fact processing incomplete information as well as it can be processed. For example, if an investor makes an investment in a company and that company issues a profit warning a week later sending the company’s stock down, rational choice theorists posit that the investor didn’t make an irrational decision but that based on the information at the time, he or she made a perfectly rational choice. Third, rational
choice theorists suggest that while we may observe irrationality in particular settings, it may not be stable over time since either institutional forces or individual learning will overcome it over a long enough period of time. Finally, rational choice theorists claim that if we observe behavior that does not meet the normative ideal of rational decision-making, no one can improve on that behavior (Kelmon 1577-1591). Richard Posner, Chief Judge on the U.S. Court of Appeals for the Seventh Circuit and Senior Lecturer at the University of Chicago School of Law, suggests that not only does behavioral economics fail to violate Rational Choice Theory but also it in fact complements the theory. According to Posner, behavioral economics suggests that due to the lack of complete information and emotional “quirk”, people often make decisions based on emotional preferences rather than rational preferences. For example, a person may choose to eat a lobster contentedly so long as he or she has not seen the lobster alive before eating it. On the other hand, that same person may refrain from eating lobster if asked to pick his or her lobster from a live tank before eating it. Behavioral economics would explain this as an emotional quirk but Posner suggest than an alternative explanation is that this person simply has different preferences for two different goods: One is a lobster seen only after being cooked and the other is a lobster seen before, in its living state, as well as after. Similarly, our observation about the favorite and opposite favorite long shot bias and the violation of CAPM in the stock market may in fact constitute perfectly rational behavior based on difference investor preferences (Posner 24). For example, suppose a fund manager loses 15% of his assets due to poor investments but outperforms his benchmark that declines by 30% at the same time. His
client is hardly going to appreciate fewer losses but is more likely going to choose to pull his money out of the stock market entirely to preserve capital. In addition, hedge fund managers who are compensated based on absolute positive returns regardless of the broader stock market are highly motivated to protect capital and avoid losses. In fact, a manager will likely choose to avoid losses over taking outsized risk for large gains. Similarly, a pension fund manager’s most important priority is preserving the value of his clients’ pensions rather than trying to generate significant returns. Therefore, for most money managers it might be perfectly rational to avoid losses at all costs rather than “swinging for the fences” by over-investing in sure shot investments as a form of insurance against losses while investing in long shot investments as a means of generating lottery ticket like returns in order to keep up with meaningful up-market movements. Similarly, a 65 year old retiree investing his retirement savings might have a preference for avoiding losses significantly more than his preference for generating outsized returns vis-à-vis the market while a 25 year old investor with a longer term investment horizon is more willing to take risk given his retirement needs are not necessary for 35 more years. These differences in preferences and risk tolerance might actually be perfectly rational given difference market participants’ risk preferences.

This difference in preference suggests that collectively investors are both risk averse and risk loving at the same time. According to Jan Zabojnik, there is overwhelming evidence that in many situations individuals exhibit an aversion towards uncertainty – homeowners buy insurance, investors need to be compensated for bearing
risk, workers like stable employment and so on. On the other hand, in many cases people appear to enjoy risk - they play the roulette wheel in casinos, buy sweepstakes, bet on horses and under-diversify their investment portfolios. Zabojnik explains, “People seem to have conflicting preferences with regard to risk.” In Principles of Economics, Alfred Marshall 1920, Marshall states “…but on the other hand, if an occupation offers a few extremely high prizes, its attractiveness is increased out of all proportion to their aggregate wage.” Several explanations have been cited for this. First, individuals may gain some “intangible” utility from the social aspects of gambling such as sitting around a casino or poker table with friends enjoying a laugh or two or the thrill of watching horses thunder around a racetrack at a horse track. This fails to explain why individuals choose to play the lottery or play online poker where social interaction is minimal at best (Zabojnik 274-285).

According to Russell Sobel and Travis Raines, rational expectations theories for the favorite longshot-bias can be generally grouped into two categories: risk preference theories and information-perception theories (Raines, Sobel 371-385). The first group of theories attributes the bias to a preference for risking among gamblers. In 1958, Friedman and Savage posited that consumers have a globally risk-averse utility function, yet over the relevant range concerning gambling and betting, the utility function becomes locally risk-loving. Friedman and Savage contend that the long-shot bias adheres to the full rationality assumption or the expected utility framework to generate both risk-averse and risk-seeking behavior by the same individual. Friedman and Savage proposed a
utility function consisting of both concave and convex segments showing that an individual with preferences described by such a utility function will accept some fair lotteries and reject others. The Friedman Savage utility function implies that most individuals derive greater utility from an increase in wealth but that up to a certain point, their marginal utility from rising wealth begins to diminish and taper off, as illustrated by the convex segments of the utility function. According to Friedman and Savage, in

![Figure 19](image)

Figure 1. The Friedman-Savage utility function with one convex and two concave segments.

between these to levels of wealth individuals go through a transition period where they measure wealth relative to one another rather than on an absolute basis. At this point,
individuals begin to derive greater utility for a given level of wealth and therefore investors’ preference for risk skews towards more risk taking with assets that have lottery like payoffs. According to Friedman and Savage, it’s this interplay between individuals that are constantly in a state of risk averting and risk taking behavior that leads to this phenomenon of the favorite and opposite favorite long-shot bias in stock markets. In contrast to behavioral economists, Friedman and Savage argue that this is perfectly rational in that as investor preference towards risk changes, so do their rational response to taking risk (Friedman, Savage 279-304).

Another explanation using risk-preference theories to explain for the long-shot and sure shot bias existing at the same time might be due to the presence of different agents with different preferences and utility curves. For example, a long only pension fund with an investment time horizon of 20-30 years and the goal of matching future plan beneficiary liabilities with the pension funds’ assets might be more concerned with asset stability and limiting downside risk rather than large returns or outperforming a benchmark. In contrast, a hedge fund manager whose salary depends on one year performance or perhaps quarter to quarter performance versus a benchmark might be willing to take more risk and investment in long shots with the idea of making large potential gains with his clients’ money. Downside protection may not be as important both because that hedge fund can protect his downside risk through hedging strategies such as options or given the fact that the manager is investing client assets rather than his
own, he might be more disposed to upside returns and less concerned with downside movements (Zabojnik 279).

Figure 20

The illustration above shows 3 different agents’ risk curves or preference for risk. Each agent is listed as C1, C2 and C3. As shown, agent C1 has a much higher tolerance for risk versus agent C3. In other words, agent C1 is willing to assume a lower level of return for the same level of risk as both agents C2 and C3. Agent C3 is the least risk averse and demands an exponentially greater rate of return for assume even a slightly greater level of risk. The point here is that C1 may act as the agent betting on the long shot while C3 is more likely to bet on the sure shot given his lower tolerance for taking
risk. In fact, agent C3’s risk free return hurdle is higher than agent C1 from the start suggesting that C3 won’t even begin taking risk until he has been guaranteed a minimum level of return from the start. Therefore, the co-existence of the long shot and sure shot bias may just be function of different agents with different risk preference curves engaging with market at the same time.

Unfortunately, recent studies conducted by Stephen LeRoy at the Federal Reserve Bank of San Francisco suggests that even assuming a “normal” level of risk aversion doesn’t explain the level of stock price volatility that exists in equity markets. According to Stephen LeRoy’s work, although recent research has moved away from the efficient capital markets assumption of “reasonable levels of risk aversion”, even after incorporating risk aversion into formal models, “the degree of volatility seen in the real world only seems implausibly high and does not satisfactorily explain the volatility of stock price movements.” This observed volatility in stock prices appears to contradict stock market efficiency and efficient market theorists. LeRoy notes Robert Shiller’s work from 1981 on stock price movements relative to changes in corporate dividends which suggests that stock price volatility is too high relative to the volatility in underlying corporate dividends under the efficient market assumption that investors have a low level of risk aversion (LeRoy 3). Shiller states that the assumption that stock prices should equal expected future dividends independent of the volatility of dividends can be justified only if investor risk aversion is excluded. If investors are risk averse, stock prices will depend on how variable dividends are in addition to their expected levels. This sort of a
measure of market efficiency implicitly treats investors as being risk neutral. According to Shiller’s work, stock price volatility implied by a given dividend model depends on how much information investors are assumed to have about future dividends. If investors cannot predict future dividend growth, they will price stocks at a constant multiple of current dividends and therefore the stock price volatility relative to dividend volatility will be zero. On the other hand, if investors have information about future dividends, then stock prices relative to dividends will vary over time. The more information about dividend growth investors have, the greater the average price variation. Therefore, the price volatility associated with perfect and complete information is the highest level of volatility that can actually occur. In variance bound tests, Shiller and others found that the observed price volatility appeared to exceed this maximum level based on complete information thereby contradicting the efficient markets model even after eliminating the assumption of risk neutrality. Shiller suggests that stocks as an asset class exhibit volatility that is too high relative to the volatility of underlying dividends (Shiller 24). Similarly, work conducted by Kevin Lansing and Stephen LeRoy in 2011 computed the stock price volatility implied by different levels of risk aversion. Like Shiller, they found that, under normal levels of risk aversion, predicted maximum stock price volatility is actually much lower than what is actually seen in the market. They also found that the higher the level of risk aversion, the higher the maximum stock price volatility. Therefore, stocks still exhibit volatility that is too high relative to efficient market predictive models even after making the assumption that investors are inherently risk averse which stands in violation of the efficient market hypothesis (LeRoy, Lansing 2).
A counter point to Shiller and LeRoy comes from the theory of rational expectations with respect to information-perception, sometimes called misperception theory, as a reason for why stock price volatility is so high relative to underlying dividend volatility even after taking into account risk-averse investor behavior. The idea behind misperception theory is that investors don’t have all of the available information needed to accurately project a company’s future prospects. In other words, investors rationally invest in stocks on expected outcomes that they believe are accurate based on the information they’ve been given or that they’ve been able to collect. The information given is either inaccurate or incomplete or both but in the end, investors make choices based on misperceptions about expected future outcomes and projections. More often than not, corporate executives and board members have information asymmetry as it relates to product demand, new products and services, and changes in corporate strategy such as acquisitions and divestments. This kind of information can often lead to dramatic changes, positive or negative, for a company’s future prospects and therefore future expectations relative to expectations today. Therefore, what may look like a long shot or sure shot investment in hindsight might have looked like a very attractive investment, in the case of the long shot, or a very poor investment, in the case of the sure shot, at that time based on the information at hand. Finally, information-perception theories for the long-shot and sure-shot bias also suggest that bettors do not perfectly absorb information. In fact, Snowberg and Wolfers suggested, through studies conducted by cognitive psychologists, people are systematically poor at discerning between small and tiny
probabilities and similarly poor at discerning high and extremely likely probabilities. Therefore, it is the representative bettor’s inability to process information correctly that leads to a favorite and opposite favorite long-shot bias (Snowberg, Wofers 723-746).

The point here is that while difference in risk preference curves and marginal utility of wealth can explain the long shot and sure shot bias in terms of rational investor expectations, stock prices exhibit volatility that is too high relative to underlying dividend and cash flow volatility. While investors are assumed to have a normal level of risk aversion, data suggests that investors have a degree of risk aversion that is higher than what can be explained by rational expectations. This may be a function of misperception theory whereby investors are making rational choices but based on incorrect or incomplete information. In this case, rational expectations theory is still relevant although more research would need to be conducted into whether the lack of information or incomplete information leads to overly optimistic or overly pessimistic future projections. Overly optimistic projections from misperception can help explain the long shot bias but not necessarily the sure shot bias. Similarly, overly pessimistic future expectations based on misinformation and misperception can help explain the sure shot bias but may not be helpful in explaining the long shot bias.
CONCLUSION

The Capital Asset Pricing Model (CAPM) states that investments with greater risk require greater returns from investors in order to compensate them for taking greater risk. Therefore, under the premise that market participants act rationally and therefore markets run efficiently, investments with higher risk should generate higher returns vis-à-vis investments with lower risk over the long run. A plethora of academic research focused on this particular topic suggests that the empirical data surrounding risk and returns contradicts the conclusions of modern portfolio theory. In fact, many studies suggest that investments with lower risk actually generate equal to or higher returns relative to investments with higher risk.

In looking at data for the S&P 500 going back 22 years between 1990 and 2012, I found that there was very low correlation between risk and returns. In fact, portfolios with very low risk generated commensurate to better returns versus portfolios with very high risk. In addition, in general portfolios that delivered higher returns with greater risk did not generate high enough returns to compensate for greater risk. In other words, there appears to be diminishing marginal returns with greater level of risk assumed by investors. It seems that beta does a poor job of predicting future returns and measuring a
company’s fundamental risk. Therefore, CAPM may be flawed in that beta does a poor job in capturing a stock’s true underlying risks.

In looking for a better measure of risk, I looked at the fundamental characteristics of each company, specifically corporate profitability and balance sheet leverage, which are commonly used by investors in assessing the underlying quality of a company. I found two important observations in looking at the empirical data. First, companies with higher levels of average long term return on equity combined with lower levels of average balance sheet leverage tend to outperform companies with lower levels of profitability and higher balance sheet leverage. This shouldn’t be a big surprise. Naturally, companies with better fundamentals should perform better than companies with relatively worse fundamentals. Interestingly, the second observation from the data is that while in general, companies with high ROEs and low leverage tend to outperform companies with low profitability and high leverage, portfolios of those companies with the highest ROE and lowest leverage and portfolios of those companies with the lowest ROE and highest leverage actually underperform on the whole other portfolios. In other words, portfolios of companies that exhibit the most extreme of characteristics in terms of ROE and leverage underperform portfolios of companies with more moderate characteristics.

One plausible explanation for this underperformance at the extremes is rooted in behavioral economic theory known as the favorite long shot bias and the opposite
favorite long shot bias. The opposite favorite long shot bias suggests that market participants tend to “over-bet” an asset and/or an investment with high probability of a payoff but low overall return if the payoff occurs, in other words, the sure winner or the sure bet. In fact, market participants go so far to secure a payoff that they actually place a higher bet on the probability of success than the actual odds would suggest. In stock market terms, investors will tend to over-value the least-riskiest stocks to the point where risk and return is no longer favorable. Similar phenomenon can be observed in horse race betting and sports drafts. The favorite long shot bias is the inverse of the opposite favorite longshot bias. This theory suggests that market participants actually “over bet” an asset and/or an investment with the lowest probability of a payoff but with significant overall returns if the payoff occurs. Similar phenomenon takes place in the purchase of insurance to insure against large potential losses with small probabilities as well as lottery ticket purchases. With respect to the stock market, this is similar to an investor purchasing penny stocks or a high-flying company with an unproven track record with the idea of making large potential returns but with a highly low likelihood of success.

On the other hand, rational expectations theory suggests that the existence of the favorite longshot bias and the opposite favorite longshot bias existing at the same time is actually perfectly rational and consistent with rational expectations theory. One of the most of interesting explanations may be that investors are both risk loving and risk averse at the same time depending on their relative marginal utility for wealth. In other words, an investor investing $100,000 of his personal money in the stock market may choose to
protect his invest from a loss at all costs, an extreme form of loss aversion, to the point where that investor will over-bet low risk stocks and exhibit characteristics of the opposite favorite long-shot bias. At the same time, if that same investor invests $1,000 of his personal money in the stock market, he or she may choose to gamble and take bigger risks investing in penny stocks and highly risky investments with the idea of accepting a small loss for a significantly large payout. In other words, at a certain point along a person’s marginal utility horizon, that investor will become risk loving or risk averse but the fact is that this investor is making a perfectly rational choice but with different levels of risk loving and risk averting behavior at different levels of investment. Additionally, different agent with different risk preferences and marginal utility of wealth can influence stock prices at the extremes. Pension investors, hedge funds, retail investors and long only mutual fund managers all have different investment time horizon, different long term and short term return expectations and therefore can have difference tolerances for risk and risk preference in general. The point is that the rational expectations theory suggests that the long shot and sure shot bias need not be an example of irrational behavior but may in fact be perfectly rational.

Regardless of the cause for long shot and sure shot investing, we find that the phenomenon of over-investing at the extremes does exist especially when looking at fundamental factors such as ROE and debt/capital ratios in terms of measuring risk. We find that beta, in fact, does a poor job of capturing a company’s fundamental risk and hence future stock price returns relative to more fundamental analysis.
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