The Low Beta Model

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Introduction

Higher risk stocks have a greater expected return than lower risk stocks if investors rationally demand a proportional return for risk. Put another way, the risky long shot should pay off more than the safer favorite. However, there is evidence that behavioral biases lead many investors to over-weight risky stocks and under-weight safer stocks. We present evidence that a portfolio of low risk stocks may generate higher returns than a portfolio of higher risk stocks.

Quantifying a Stock's Risk with Beta

One can think of a stock generally having two types of risks, unsystematic risk and systematic risk. Unsystematic risk is company specific. For example, company specific risk might be financial statement fraud or a company's products falling out of favor. This unsystematic risk can be reduced through diversification. Systematic risk, or market risk, describes the market's influence on a particular stock. A bear market tends to drag stocks down and vice versa for a bull market.

A stock's beta (β) is a measure of its sensitivity to the returns on the overall stock market. It is a measure of systematic risk that cannot be avoided by diversification.[1] An asset with a beta of .5, on average, would have half the magnitude of price fluctuations compared to the stock market. A beta greater than 1 means the asset is riskier than the stock market.

The Low Volatility Anomaly

Andrea Frazzini and Lasse Pedersen (2011), in their research paper *"Betting against Beta,"* conclude that it does not pay to take risks associated high beta stocks. Their findings are at odds with the principle that investors, overall, demand proportionately high returns for holding a portfolio of high risks stocks. Frazzini and Pedersen contend that because many investment managers have investment policies that prohibit leverage, they attempt to boost their returns by overweighting riskier assets. Because investors bid up the prices of riskier stocks, the expected returns from them are too low. Academics refer to this as "Low Volatility Anomaly".

[1] Please see the Glossary for a complete description of *Beta* and other terms that we bounce around in our paper.

Our Testing Confirms the Low Beta Anomaly

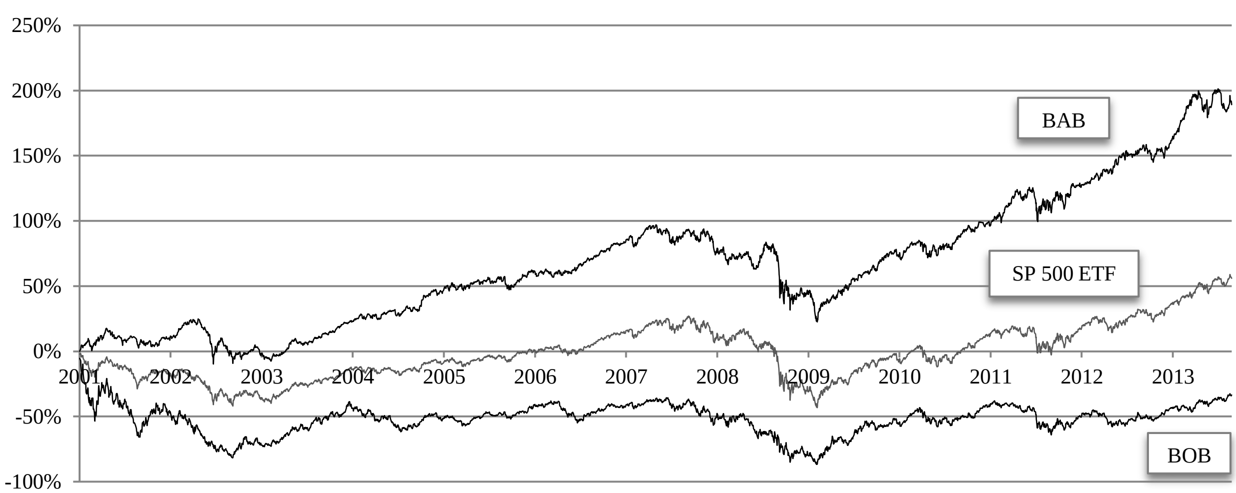
Frazzini and Pedersen constructed 10 portfolios comprised of U.S. Equities sorted by their betas. Portfolio 1, the Betting against Beta (BAB) portfolio, consisted of equal weights of 10% of stocks that had the lowest historical beta, the bottom decile. Portfolio 10, the Betting on Beta (BOB) portfolio held the top decile beta stocks in equal weights. In an 86-year investment simulation with monthly rebalancing to equal weights, the BAB portfolio scored higher risk adjusted returns.

Using the Portfolio 123 back tester, we replicated the Frazzini and Pedersen's findings. Portfolios of lower beta stocks outperformed portfolios of higher beta stocks. We tested 12 years' of data (February 1, 2001 through September 26, 2013) on S&P 500 Index constituent stocks.[2] We chose the S&P 500 because the index is widely followed and the stocks within the index are highly liquid. Portfolio123 utilizes a point-in-time database for the S&P 500. Point-in-time means the database has the historically correct index constituents for any point in time.

First, we created two portfolios: a Betting <u>against</u> Beta (BAB) Portfolio of the 50 lowest beta stocks and a Betting <u>on</u> Beta (BOB) Portfolio of the 50 highest beta stocks. The portfolios were rebalanced every 28 days. We included .2% for slippage and commissions on each trade.

In Figure 1 and Table 1, we see that the BAB Portfolio of low beta stocks outperformed the S&P 500 ETF (SPY), which in turn outperformed the BOB Portfolio of high beta stocks.

Figure 1 – Back-test Total Returns: 02/01/2001 - 09/26/2013



[2] While Portfolio 123 has security data going back as far as 1999, we felt that the large number of N/A's returned prior to February 2001 in our Analyst Surprise and Analyst Next Fiscal Year Estimate nodes was too great to accurately simulate the model's performance.

We also ran the same test excluding stocks in the S&P 500 Utilities Sector (BAB ex-Utilities) shown in Figure 2 and Table 1. We expected that by throwing out utility stocks, our hypothetical return would diminish.

Figure 2 – Back-test Total Returns: 02/01/2001 - 09/26/2013

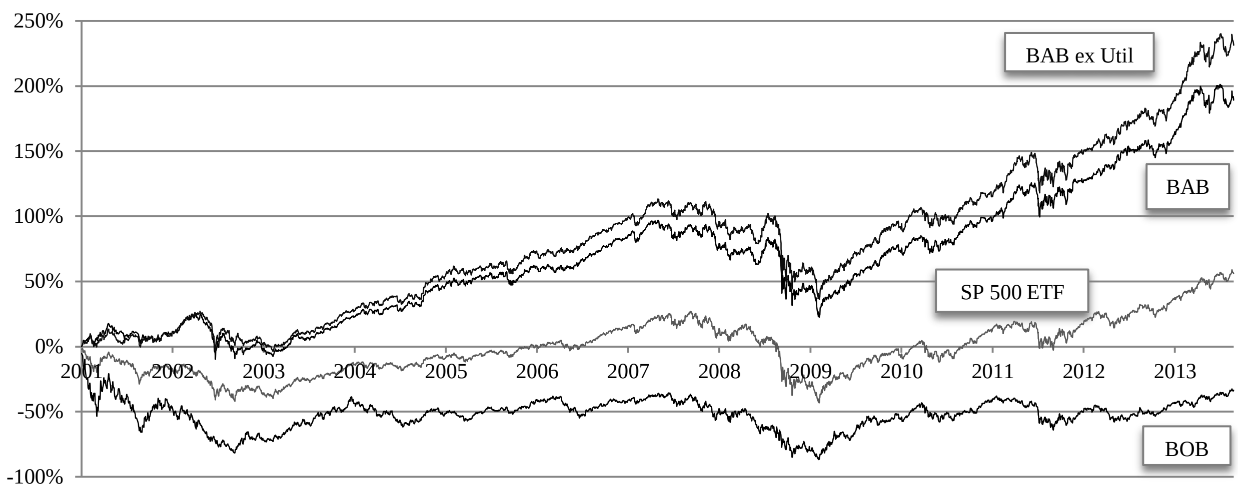


Table 1 – Back-test Risk & Return Measures: 02/01/2001 - 09/26/2013

	Annualized Return	Max Drawdown	Sharpe Ratio	Sortino Ratio	Standard Deviation	R^2	Beta	Alpha
BAB Portfolio	8.77%	-37.79%	.30	.38	16.84%	.65	.54	4.93%
BAB ex-Util.	9.97%	-36.16%	.37	.49	16.65%	.69	.55	6.08%
BOB Portfolio	-3.19%	-86.71%	-.13	-.17	54.91%	.72	1.85	-6.46%
S&P 500 ETF	3.61%	-55.19%	-.01	-.01	25.16%	-	-	-

To our surprise, the BAB ex-Utilities Portfolio outperformed. There are a couple of implications. First, we gained confidence in the robustness of the BAB model because we removed a potential hindsight bias. We knew that the utility sector had outperformed the broader market over the 12-year test period. Second, a common criticism to the BAB model is that it is industry dependent, "going long stodgy (but perhaps ultimately profitable) industries and by an assumption that the returns are driven by value effects (Asness, Frazzini, & Pedersen, 2013)."

We wondered what would happen if we removed utilities and staples, the sectors containing the stodgiest and most value tilted industries, from our universe. See Table 2.

Table 2 – Back-test Risk & Return Measures: 02/01/2001 - 09/26/2013

	Annualized Return	Max Drawdown	Sharpe Ratio	Sortino Ratio	Standard Deviation	R^2	Beta	Alpha
BAB Portfolio	8.77%	-37.79%	.30	.38	16.84%	.65	.54	4.93%
BAB ex-Util.	9.97%	-36.16%	.37	.49	16.65%	.69	.55	6.08%
BAB ex-Util. & ex-Staples	10.75%	-44.50%	.36	.46	19.67%	.69	.65	6.85%
BOB Portfolio	-3.19%	-86.71%	-.13	-.17	54.91%	.72	1.85	-6.46%
S&P 500 ETF	3.61%	-55.19%	-.01	-.01	25.16%	-	-	-

After eliminating two of the least volatile sectors in the S&P 500 universe, the BAB ex-Utilities and Staples portfolio (BAB ex-Util. & ex-Staples, Table 2, above) consisted of the lowest beta stocks of the most cyclical and growth tilted industries and still produced superior absolute and risk adjusted returns compared to the S&P 500 ETF.

Might the Low Volatility Anomaly Persist in the Future?

From all the published research that we have read, the evidence of the Low Volatility Anomaly's historical existence is robust. The question of whether the anomaly will continue in the future depends on the forces of arbitrage. That is to say, will enough participants bet against beta in the future to arbitrage away the strategy's excess returns? Baker, Bradley, and Wurgler (2010) argue that the Low Volatility Anomaly will persist because of behavioral biases and benchmarking.

Behavioral Biases

Human brains are hardwired with certain predispositions, or biases. On a grand scale, investor behavioral biases push stock prices far above and below intrinsic values. Baker et al credit Preference for Lotteries, Overconfidence, and Representativeness as the investor biases at work in the Low Volatility Anomaly.

Table 3 - Examples of Behavioral Biases

Behavioral Bias	Example
Preference for Lotteries	Rationally, people should not play games with a negative expected return. *I am going to play the lottery anyway, because… you never know.*
Overconfidence	Investors and analysts tend to be overconfident in the precision of their forecasts. *I am 90% confident that XYZ.Q will earn $9.314 per share next year.*
Representativeness	Believing a high beta stock is representative of a good investment. *My brother-in-law's cousin bought a stock just like this one and he made a killing.*

The Tourist and the Reluctant Shark

Behaviorally biased investment decisions initially generate excess returns for institutional investment managers savvy enough to identify and exploit them. However, as more savvy investors press their advantage, they devour excess returns to a point of non-existence. At least that is how things should work. The Low Volatility Anomaly may be more persistent. This is analogous to a shark unwilling to pick off the portly tourist bobbing just off the beach.

An institutional investment manager is most often evaluated by his or her Information Ratio (IR), or the average excess returns to a benchmark divided by the standard deviation of these excess returns (tracking error). By focusing on excess returns while minimalizing the tracking error, i.e., keeping the portfolio's beta close to 1, institutional investment managers are disincentivized from overweighting low beta stocks (Baker et al, 2010). Furthermore, because of leverage constraints, many institutional managers cannot lever up low beta portfolios to achieve risk parity with their benchmark (Frazzini et al, 2011).

Exploiting the Low Volatility Anomaly: The Low Beta Model

We created the Low Beta (LB) Model to exploit the Low Volatility Anomaly. The LB Model selects boring stocks. We purposely avoid stocks that exhibit lottery like return payoffs, enthusiastic analyst profit projections, and the antithesis of what many investors think makes for a good stock investment. In the LB Model simulation, presented later, we will see if our model for selecting boring stocks has the potential for producing exciting returns.

How Boring Can We Get? - The LB Model Opportunity Set

The LB Model opportunity set includes approximately 250 stocks with betas less than the median beta for the S&P 500. We calculate up to a 750-day daily return beta, with a minimum of 500 days of data. Stocks with less than 500 days of return data are not eligible for the LB Model portfolio.

"Yawn" - The LB Model's 3-Factor Ranking System

The LB Model ranks the 250 or so stocks in its opportunity set based on a three equally weighted factors. Subject to sector weight and data availability constraints, the LB Model starts by purchasing the 30 highest ranked stocks. We detail these constraints further on. For the LB Model's first factor rank, and in the spirit of the BAB strategy, lower beta stocks receive a higher rank score.

The second factor rank uses inputs related to analyst expectations. It has two equally weighted nodes. The first node looks at the absolute percentage surprise from the stock's previous earnings announcement. Any earnings surprise, good or bad, counts against the stock's rank score. The second node looks at the next fiscal year analyst expectations. There must be five or more analyst estimates available. Relatively large disagreement among analysts on a company's next fiscal year results reduces the stock's ranking. We assume that large earnings surprises and analyst disagreements are indicative of higher future betas.

For the third factor rank, the LB Model utilizes the 300-day and 150-day momentum formula that we first developed in creating the Select Directional ETF Model (SDM). For more information, download the SDM whitepaper and actual performance from our website, www.successfulportfolios.com. Broadly stated, stocks demonstrating recent persistent relative price strength receive a higher rank in the LB Model.

The LB Model Diversification Requirements and Trading Rules

To help neutralize the industry and value effects and not hold too high a concentration of any one sector, we added sector-weighting constraints as the first buy rule (Table 4). The second buy rule requires a stock to have at least 5 analyst estimates for the next fiscal year.

Table 4 - LB Model Sector Weighting and Trading Rules

Buy Rules	1	Buy highest ranked stock as long as its incremental sector weighting does not exceed 20% of the portfolio, and…
	2	there are at least 5 next fiscal year recommendations.

Sell Rules	1	Sell lowest ranked stock(s) if their sector weight is greater than 25% of the portfolio, or…
	2	if a stock's ranking falls below the 50th percentile, or…
	3	if an individual stock's weight increases to 6.6% of the NAV of the portfolio, sell half of the position.

The Hypothetical, Not-So-Boring Results of a Strategy of Selecting Boring Stocks

With our ranking factors and trade rules in place, we directed Portfolio123 to run a simulation of how the LB Model would have performed beginning February 1, 2001. Once again, we included .2% commissions and slippage for each trade. Management fees of 1% per year were also deducted. Figure 3 and Table 5 detail the simulated risk and return measures.

Figure 3 - Simulated LB Total Returns (Net of Fees): 02/01/2001 – 09/26/2013

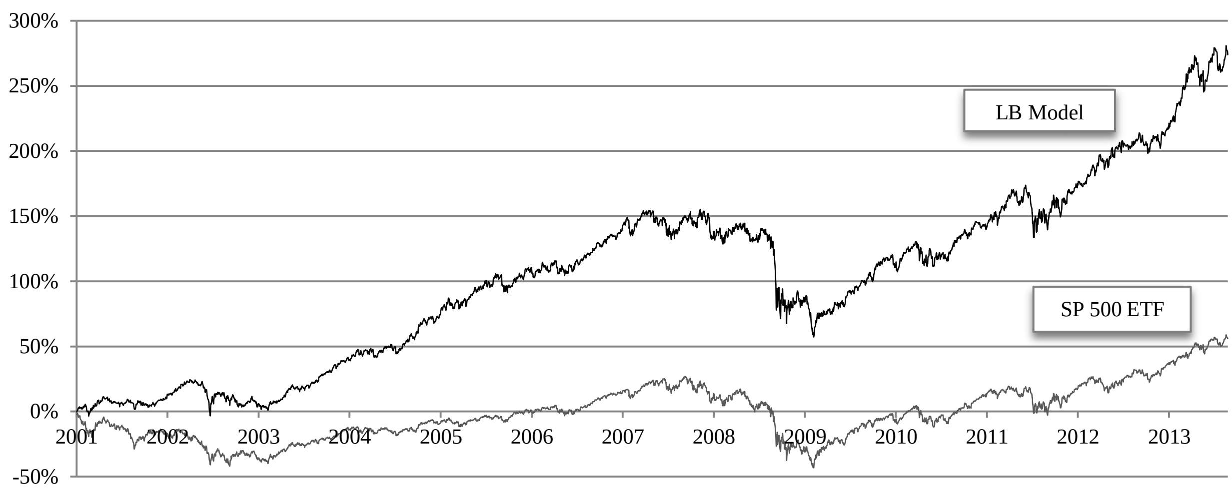


Table 5 – Simulated LB Risk and Return Measures: 02/01/2001 – 09/26/2013

Since Inception	LB	S&P 500 ETF	Trailing 3 Year	LB	S&P 500 ETF
Total Return (%)	276.18	56.57	Total Return (%)	63.90	58.08
Annualized Return (%)	11.04	3.61	Annualized Return (%)	17.90	16.49
Max Drawdown (%)	-38.35	-55.19	Max Drawdown (%)	-14.71	-18.61
Standard Deviation	18.17	25.16	Standard Deviation (%)	15.76	19.89
Sharpe Ratio	0.40	-0.01	Sharpe Ratio	0.99	0.71
Sortino Ratio	0.53	-0.01	Sortino Ratio	1.33	0.89
Correlation with Benchmark	0.85	-	Correlation with Benchmark	0.92	-
R-Squared	0.72	-	R-Squared	0.84	-
Beta	0.61	-	Beta	0.73	-
Alpha (%) (annualized)	7.13	-	Alpha (%) (annualized)	5.19	-

The simulated LB Model returned a not-so-boring 276.2% vs. 56.5% on the S&P 500 ETF. The average holding period of a stock during the simulation was 511 days. That would qualify for lower long-term capital gains tax rates. Annualized turnover was a reasonable and tax-efficient 53.6%. Realized winning trades were 56.9% (128/225) of total trades. Overall winning trades (including unrealized gains) were 60.4% (154/255). Remember that past or simulated returns are not necessarily indicative of future results.

We ran regression analyses[3] based on the Capital Asset Pricing Model (CAPM) and the Fama-French Model (Appendix 1).[4] The LB Model's alpha (outperformance) was statistically significant relative to returns on the CRSP NYSE/AMEX/NASDAQ Value-Weighted Market Index with a *P- value* of .0019.

Running additional simulations for different market regimes provides an idea of how the LB Model might perform in future bull and bear markets. In Table 6, we can see the LB Model outperformed the S&P 500 ETF in absolute return and risk adjusted return in 3 out of 4 periods.[5]

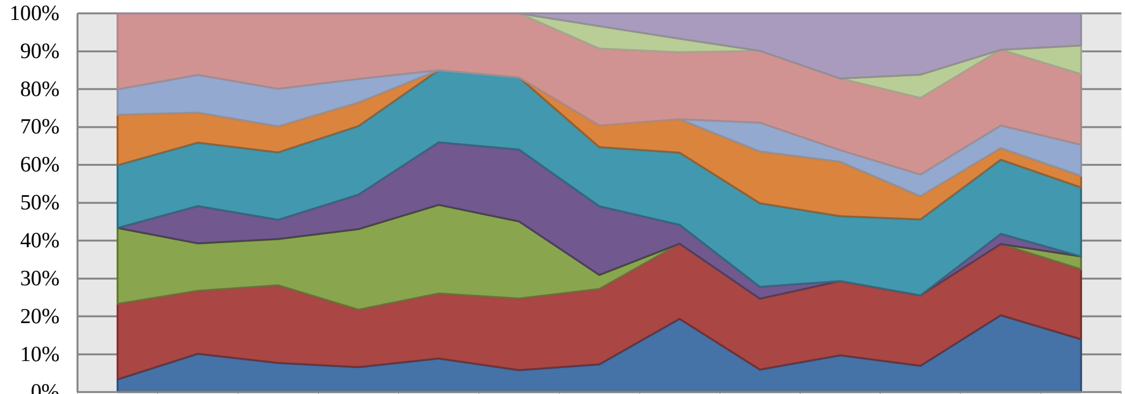
Table 6 - Simulated LB Model Performance in Bear and Bull Markets

Bear Markets	LB	S&P 500 ETF		LB	S&P 500 ETF
Inception Date	02/01/2001			10/12/2007	
End Date	10/04/2002			03/06/2009	
Total Return (%)	8.33	-40.02		-40.55	-54.61
Annualized Return (%)	4.91	-26.37		-31.04	-43.14
Max Drawdown (%)	-22.62	-39.99		-41.45	-54.31
Standard Deviation	18.38	28.91		32.35	46.16
Sharpe Ratio	0.0	-1.08		-1.07	-1.01
Sortino Ratio	0.0	-1.71		-1.51	-1.42
Correlation with Benchmark	.62	-		.94	-
R-Squared	.39	-		.88	-
Beta	.40	-		.66	-
Alpha (%) (annualized)	11.90	-		-3.72	-
Bull Markets	LB	S&P 500 ETF		LB	S&P 500 ETF
Inception Date	10/04/2002			03/06/2009	
End Date	10/12/2007			09/26/2013	
Total Return (%)	112.39	111.45		123.82	172.00
Annualized Return (%)	16.18	16.08		19.33	24.55
Max Drawdown (%)	-9.13	-14.18		-14.55	-18.61
Standard Deviation	13.34	16.38		15.96	22.25
Sharpe Ratio	.88	.71		1.04	.98
Sortino Ratio	1.28	1.04		1.45	1.33
Correlation with Benchmark	.81	-		.90	-
R-Squared	.65	-		.80	-
Beta	.66	-		.64	-
Alpha (%) (annualized)	3.93	-		2.56	-

[3] We thank Wesley Gray, PH.D. for the very informative Excel tutorial on calculating and analyzing Fama-French Alpha found at http://turnkeyanalyst.com/2012/01/12/alphacalculation/.
[4] Kenneth French provides a trove of highly useful return data at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html
[5] We present a portion of the first bear market in our period simulation because of a lack of analyst projection and surprises data prior to 02/2001. Nonetheless, the S&P 500 ETF still declined 40% during this abbreviated period.

Looking at the historical allocation over the simulation, Table 7, we see the historically low beta Utility, Staples, and Health Care Sectors, comprised around 55% of the portfolio on average. It is worth noting that the LB Model portfolio held no Tech stocks in the immediate aftermath of the internet bubble bursting. Additionally, the LB Model was very underweight the Financial Sector, one of the worst performing sectors throughout the carnage of 2008 and 2009.

Table 7 - Simulated LB Model Sector Allocation: 02/01/2001 - 09/26/2013



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
InfoTech	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	3.4%	6.7%	9.9%	17.2%	16.2%	9.6%	8.5%
Telecom Services	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.9%	3.6%	0.0%	0.0%	6.1%	0.0%	7.6%
Utilities	20.0%	16.2%	19.9%	17.3%	15.0%	16.9%	20.3%	17.7%	19.0%	18.9%	20.2%	20.0%	18.7%
Materials	6.7%	9.9%	9.9%	6.2%	0.0%	0.0%	0.0%	0.0%	7.6%	3.1%	5.7%	6.0%	8.2%
Industrials	13.3%	7.9%	6.9%	6.2%	0.0%	0.0%	5.7%	8.8%	13.7%	14.4%	6.2%	3.1%	3.1%
Health Care	16.6%	16.7%	17.8%	18.1%	19.1%	19.1%	15.6%	19.1%	22.1%	17.1%	20.1%	19.6%	18.2%
Financials	0.0%	9.8%	5.1%	9.1%	16.5%	19.0%	18.1%	5.0%	3.1%	0.0%	0.0%	2.7%	0.0%
Energy	20.1%	12.5%	12.2%	21.3%	23.4%	20.4%	3.7%	0.0%	0.0%	0.0%	0.0%	0.0%	3.4%
Consumer Staples	19.9%	16.6%	20.5%	15.2%	17.2%	18.9%	19.9%	19.8%	18.7%	19.6%	18.6%	18.8%	18.5%
Consumer Discr	3.4%	10.1%	7.7%	6.6%	8.9%	5.8%	7.3%	19.4%	5.9%	9.7%	7.0%	20.3%	14.0%

Conclusion

Based on the findings of recent academic research and the results of our simulations, we believe that the Low Beta Model may earn favorable, tax efficient, risk adjusted returns for investors when followed over a complete market cycle. Lower beta stocks are defensive in nature and should not suffer drawdowns as great as the S&P 500 Index in bear markets. By combining our novel ranking system and disciplined rebalancing rules to exploit the Low Volatility Anomaly, we believe the LB Model has the potential to outperform the overall market in periods of rising stock prices. In fact, beginning September 20, 2013 with $215,000 of funds from existing clients and our own personal funds, we launched the LB Model . Please see Appendix 2 for the LB's initial holdings. Going forward, the performance of LB will be available on our website, [www.successfulportfolios.com.](http://www.successfulportfolios.com)

References

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Baker, M., Bradley, B., & Wurgler, J. (2010, March). *Benchmarks as Limits to Arbitrage: Understanding the Low Volatility Anomaly.* Retrieved from Social Science Research Network.

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Appendix 1 CAPM and Fama-French Model Regressions

Capital Asset Pricing Model

Regression Statistics	
Multiple R	0.85257704
R Square	0.726887609
Adjusted R Square	0.726801698
Standard Error	0.49710962
Observations	3181

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2090.839641	2090.839641	8460.896637	0
Residual	3179	785.5880415	0.247117975		
Total	3180	2876.427682			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Alpha	0.027314566	0.008814944	3.098666025	0.001960931	0.010031014	0.044598118	0.010031014	0.044598118
Mkt-RF	0.6170988	0.006708826	91.98313235	0	0.603944735	0.630252865	0.603944735	0.630252865

Fama French 3 Factor Model

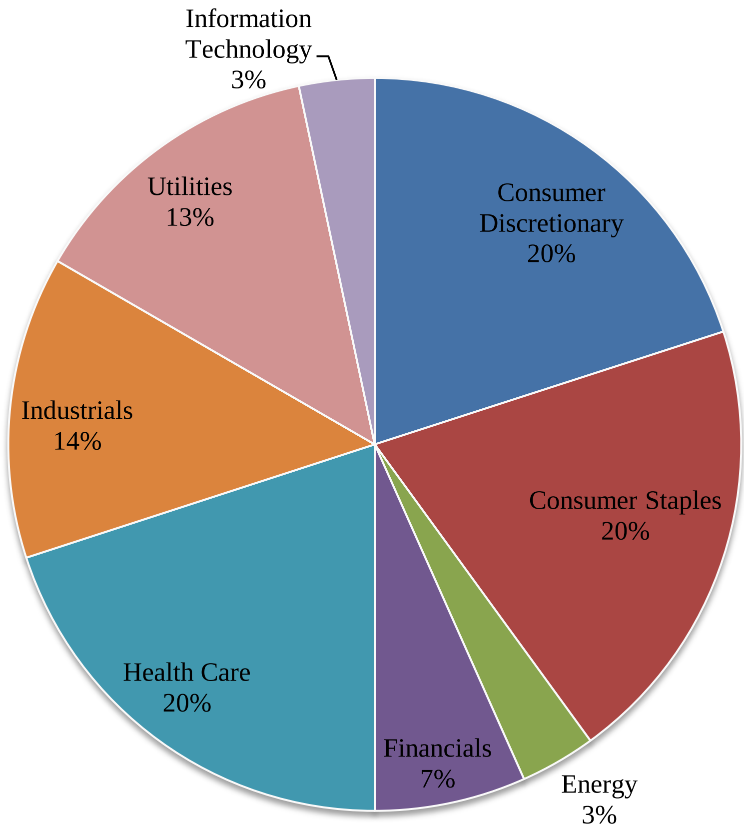
Regression Statistics	
Multiple R	0.854058637
R Square	0.729416155
Adjusted R Square	0.729160646
Standard Error	0.494958805
Observations	3181

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2098.11282	699.3709401	2854.759153	0
Residual	3177	778.3148622	0.244984218		
Total	3180	2876.427682			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Alpha	0.02729337	0.008784222	3.10709021	0.001906077	0.01007005	0.044516691	0.01007005	0.044516691
Beta w/ Mkt-RF	0.61536682	0.006810771	90.35200734	0	0.602012867	0.628720773	0.602012867	0.628720773
Beta w/ SMB	-0.05630611	0.015393557	-3.65777105	0.000258547	-0.086488424	-0.02612379	-0.086488424	-0.026123791
Beta w/ HML	0.058026798	0.015177721	3.823156199	0.000134282	0.028267674	0.087785921	0.028267674	0.087785921

Appendix 2 –The LB Model Portfolio - Inception: 09/20/2013



Ticker	Name	Stock Sector	Industry Group	% Fwd Div Yld	Equity Style Box
TWC	Time Warner Cable Inc	Communication Services	Communication Services	2.19	Large Growth
HAS	Hasbro, Inc.	Consumer Cyclical	Travel & Leisure	3.2	Mid-Cap Value
NKE	Nike, Inc. Class B	Consumer Cyclical	Manufacturing - Apparel & Furniture	1.11	Large Growth
ORLY	O'Reilly Automotive Inc	Consumer Cyclical	Autos	0	Mid-Cap Growth
TJX	TJX Companies	Consumer Cyclical	Retail - Apparel & Specialty	0.99	Large Growth
CAG	ConAgra Foods, Inc.	Consumer Defensive	Consumer Packaged Goods	3.16	Mid-Cap Value
CL	Colgate-Palmolive Company	Consumer Defensive	Consumer Packaged Goods	2.14	Large Growth
GIS	General Mills, Inc.	Consumer Defensive	Consumer Packaged Goods	3.04	Large Core
HSY	The Hershey Company	Consumer Defensive	Consumer Packaged Goods	2	Large Growth
KR	Kroger Co	Consumer Defensive	Retail - Defensive	1.54	Large Core
MDLZ	Mondelez International Inc	Consumer Defensive	Consumer Packaged Goods	1.69	Large Core
SE	Spectra Energy Corp	Energy	Oil & Gas - Midstream	3.45	Large Value
AON	Aon plc	Financial Services	Brokers & Exchanges	0.92	Large Growth
MMC	Marsh & McLennan Companies, Inc.	Financial Services	Brokers & Exchanges	2.18	Large Growth
ABC	AmerisourceBergen Corp	Healthcare	Medical Distribution	1.32	Mid-Cap Core
AMGN	Amgen Inc	Healthcare	Biotechnology	1.63	Large Core
BMY	Bristol-Myers Squibb Company	Healthcare	Drug Manufacturers	2.86	Large Core
GILD	Gilead Sciences Inc	Healthcare	Biotechnology	0	Large Growth
JNJ	Johnson & Johnson	Healthcare	Drug Manufacturers	2.87	Large Value
MDT	Medtronic, Inc.	Healthcare	Medical Devices	1.94	Large Core
COL	Rockwell Collins, Inc.	Industrials	Aerospace & Defense	1.67	Mid-Cap Value
LLL	L-3 Communications Holdings Inc	Industrials	Aerospace & Defense	2.29	Mid-Cap Value
NLSN	Nielsen Holdings NV	Industrials	Business Services	2.09	Mid-Cap Growth
WM	Waste Management Inc	Industrials	Waste Management	3.37	Large Value
FIS	Fidelity National Information Services, Inc.	Technology	Application Software	1.85	Mid-Cap Core
TRIP	TripAdvisor Inc	Technology	Online Media	0	Mid-Cap Growth
AEP	American Electric Power Co Inc	Utilities	Utilities - Regulated	4.3	Large Value
CMS	CMS Energy Corp	Utilities	Utilities - Regulated	3.68	Mid-Cap Value
NI	NiSource Inc	Utilities	Utilities - Regulated	3.11	Mid-Cap Value
XEL	Xcel Energy Inc	Utilities	Utilities - Regulated	3.85	Mid-Cap Value
				2.15	

Portfolio 123’s Glossary

https://www.portfolio123.com/doc/doc_risk_glossary.jsp

Alpha vs. Benchmark Index

Alpha is another statistic in Modern Portfolio Theory (MPT) generated from a linear regression of the fund's returns less the risk free rate against the market's returns less the risk free rate. It measures the difference between the fund's actual returns and its expected performance given its level of risk (as measured by beta).

Alpha is frequently used to measure manager or strategy performance. A positive alpha figure indicates the fund has performed better than its beta would predict. In contrast, a negative alpha indicates a fund has underperformed given the expectations established by the fund's beta. Some investors see the alpha as a measurement of the value added or subtracted by a fund's manager/strategy.

However, there are limitations to alpha statistic's ability to accurately depict a manager's added or subtracted value. In some cases, a negative alpha can result from the expenses that are present in the fund figures but are not present in the figures of the comparison index. Alpha is dependent on the accuracy of beta: If the investor accepts beta as a conclusive definition of risk, a positive alpha would be a conclusive indicator of good fund performance. Of course, the value of beta is dependent on another statistic, known as R-squared.

For Alpha, the calculation is listed below.
Alpha = (Fund Return - Treasury) - ((Beta x (Benchmark - Treasury))
Benchmark = Total Return of Benchmark Index
Treasury = Return on 13-week Treasury Bill

Annualized Benchmark Return

This is the annualized return on the benchmark index (e.g. Standard and Poor's 500).

Annualized Return

This is the annualized total return on an asset. A total return can be annualized in the expression:

Annual ret. = (Tot. Ret. + 1)^(365.25 ⁄ days) - 1

Annualized Turnover

The rate of trading activity in a fund's portfolio of investments, equal to the lesser of purchases or sales, for a year, divided by average total assets.

Beta vs. Benchmark Index

Beta is another statistic in Modern Portfolio Theory (MPT) generated from a linear regression of the fund's returns less the risk free rate against the market's returns less the risk free rate. It measures the fund's sensitivity to market movements. For example, a fund that has a beta of 1.10 means that for every return in the S&P 500 (or the chosen benchmark), the fund's returns, on average, will be 1.10 * the benchmark return. So if the S&P returns 10%, the fund will return 11%. The reverse is true if the benchmark declines. If the benchmark returns -10%, the fund will return -11%. Conversely, a beta of 0.85 indicates that the fund has performed 15% worse than the index in up markets and 15% better in down markets. Therefore, by definition, the beta of the benchmark is 1.

A low beta does not mean that the fund has a low level of volatility, though; rather, a low beta means only that the fund's market-related risk is low. A specialty fund that invests primarily in gold, for example, will often have a low beta (and a low R-squared), relative to the S&P 500 index, as its performance is tied more closely to the price of gold and gold-mining stocks than to the overall stock market. Thus, though the specialty fund might fluctuate wildly because of rapid changes in gold prices, its beta relative to the S&P may remain low.

Correlation

The correlation coefficient is a measure of the strength of the linear relationship between two random variables, where the value 0 indicates independent variables, and 1 completely correlated variables. So, intuitively, this can be used to determine how the returns on a fund and returns on a benchmark are correlated. By convention, correlation is denoted by the greek letter ρ, and the coefficient used here is found by dividing the covariance of the two variables by the product of their standard deviations.

Maximum Drawdown

Maximum Drawdown can be loosely defined as the largest drop from a peak to a bottom in a certain time period.

R-Squared vs. Benchmark Index

The R-Squared statistic is computationally the square of the correlation statistic (so, ρ2). Conceptually, it represents the percentage of the fund's returns that are explained by the returns of the benchmark. An R-squared of 1 means that the fund's returns are completely explained by the returns of the index. Conversely, a low R-squared indicates that very few of the fund's returns are explained by the returns of benchmark index. For example, An R-Squared of 50% means that 50% of the fund's returns can be explained by the benchmark's returns. Therefore, R-squared can be used to judge the significance of the fund's beta or alpha statistics. Generally, a higher R-squared will indicate a more useful beta figure. If the R-squared is lower, then the beta is less relevant to the fund's performance.

Sharpe Ratio

The Sharpe ratio is a risk-adjusted measure developed by Nobel Laureate William Sharpe. It measures the return per unit of risk. In other words, it measures how efficiently the fund is performing relative to its level of risk - the higher the Sharpe ratio, the higher the return given its risk. The Sharpe Ratio is calculated as the ratio of return of the fund above the risk-free return to annualized standard deviation. Risk-free return is the average monthly return of the 10Y Note over the appropriate period.

Sharpe Ratio = (Annualized Return - Risk Free Return) ⁄ Annualized Std. Dev.

Sortino Ratio

This ratio is computationally very similar to the Sharpe Ratio, but divides from the excess return of the portfolio by the standard deviation of the negative returns. The Sortino Ratio therefore uses downside standard deviation as the proxy for risk for investors, instead of using standard deviation of all the fund's returns, as this number includes upside standard deviation. This in effect removes the negative penalty that the Sharpe Ratio imposes on positive returns.

To help you intuitively use this ratio, imagine a hypothetical portfolio, Portfolio A, which never experiences negative returns. However, Portfolio A has incredible standard deviation in its positive returns: one day it returns 0.1% and another 1000%. The standard deviation of Portfolio A will therefore be very large. When measured by Sharpe Ratio, Portfolio A will have a low ratio, because it is symmetric in its treatment of upside and downside deviation. However, the Sortino Ratio of Portfolio A will be infinite! This is the case because there is zero standard deviation in negative returns. The Sortino Ratio only considers downside standard deviation as important.

Similarly, imagine Portfolio B, where there are only negative returns. In this case, the Sharpe Ratio and the Sortino Ratio will be exactly the same.

Therefore, the higher the Sortino Ratio, the better the risk adjusted (as measured by downside standard deviation) returns are for your portfolio.

Standard Deviation (Volatility)

This statistical measurement of dispersion about an average depicts how widely a model or simulation returns are varied over a certain period of time. When a fund has a high standard deviation, the predicted range of performance is wide, implying greater volatility.

Investors can use the standard deviation of historical performance to try to predict the range of returns that are most likely in the future. Since a model's returns are assumed to follow a normal distribution, then approximately 68% of the time the returns will fall within one standard deviation of the mean, and 95% of the time within two standard deviations. For example, for a fund with a mean annual return of 10% and a standard deviation of 2%, you would expect the return to be between 8% and 12% about 68%of the time, and between 6% and 14% about 95% of the time.

At Portfolio123, the standard deviation is computed using the three year trailing weekly returns, and since inception. The results are then annualized.

Total Return

The total return on a fund is expressed as a percentage. That is, it is calculated as a simple return in the formula:

Tot. Ret. = (Ending capital ⁄ Starting Capital) - 1.

At Portfolio123, we calculate the total return on the fund since it's inception, and for the trailing day, week, four weeks, thirteen weeks, twenty-six weeks, year and three years.

Year to Date

This is the total return on an asset since the beginning of the financial year.

Notes on Portfolio123's calculations

We only calculate risk statistics for portfolios and simulations with over 6 month's worth of data. On the "Risk" page we display the Modern Portfolio Theory and Volatility measurements for that portfolio or simulation, for two time periods:

1. from inception to end date
2. for a three year period beginning three years before the end date, given that the inception date for the fund is more than three years before the end date.