# Low-Volatility Cycles: The Influence of Valuation and Momentum on Low-Volatility Portfolios

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**Abstract**

Research showing that the lowest risk stocks tend to outperform the highest risk stocks over time has led to rapid growth in so-called low-risk equity investing in recent years. We examine the performance of the low-risk strategy previously considered in the literature and of a beta-neutral low-risk strategy more relevant to practice. We demonstrate that the historical performance of low risk investing, like any quantitative investment strategy, is time-varying. We find that both of our low-risk strategies exhibit dynamic exposure to the well-known value, size, and momentum factors and appear to be influenced by the overall economic environment. Our results suggest time-variation in the performance of low-risk strategies is likely influenced by the approach to constructing the low-risk portfolio strategy and by the market environment and associated valuation premia.

[1] The views and opinions expressed herein are those of the authors and do not necessarily reflect the views of AQR Capital Management, LLC and its affiliates.

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# Low-Volatility Cycles: The Influence of Valuation and Momentum on Low-Volatility Portfolios

## Introduction

In what is often referred to as the "low-volatility" anomaly, researchers have shown that measures of prior stock price variability, including total return volatility, idiosyncratic volatility, and beta relate to future performance but not necessarily in the way theory suggests– that investors demand higher returns as compensation for higher expected risk. Researchers, instead, have found that, empirically, the lowest risk stocks tend to outperform the highest risk stocks [Black (1972), and Black, Jensen, and Scholes (1972)]. The finding of a negative risk-return trade-off contradicts the most basic principle of financial economics and in so doing suggests the possibility of a profitable trading strategy that buys low volatility stocks and sells-short high volatility stocks. Consequently, a growing number of researchers continue to examine the existence and possible explanations for the anomaly [see, e.g., Ang, Hodrick, Xing, and Zhang (2006 and 2009), Blitz and Vliet (2007), Clarke, de Silva, and Thorley (2006, 2014), Frazzini and Pedersen (2014), Baker, Bradley, and, Wurgler (2011), Li, Sullivan, and Garcia-Feijoo (2013, 2014)].

The low-volatility anomaly has had a dramatic impact on the theory and practice of investment management. In practice, investors have seen an explosion of strategies designed to "take advantage" of the outperformance of low-volatility stocks. In just the past few years, investors have allocated more than $10 billion to low volatility mutual funds and ETFs with strong growth also observed in institutional portfolio allocations.[2] Most of the existing low-volatility strategies, however, are seemingly constructed

[2] See "High Hopes for 'Low Volatility' Funds", *Wall Street Journal* (April 6, 2014) http://online.wsj.com/news/article_email/SB10001424052702303824204579421602356517282-lMyQjAxMTA0MDAwNzEwNDcyWj

purely on the basis of risk, with little attention paid to the other characteristics known to affect portfolio performance. In this paper, we attempt to quantify the time-varying nature of low-risk strategies to include an understanding of the impact of the macroeconomy as well as portfolio characteristics such as size, value, and momentum.

Low volatility strategies discussed in the literature typically approach low volatility investing with models designed to separate out the high volatility stocks from the low volatility stocks via the creation of "risk quintiles." The strategies define risk as either idiosyncratic volatility employing a multi-factor model controlling for the well-known size (large vs. small) and style (growth vs. value) characteristics; or as beta from the CAPM. For this paper, we focus on beta as defined by the coefficient on the market factor from the CAPM following Baker, Bradley, and Wurgler (2011). We employ two low-risk strategies based on CAPM beta and explore their dynamic performance.

Within the low-volatility literature, the discussion of how low-volatility portfolios interact with the well-known characteristics of value, size, and momentum (Asness 1997; Fama and French, 1992, 1993; Jegadeesh and Titman, 1993, 2001) remains largely absent. We suggest that omitting these characteristics identified in the literature, and now widely understood to impart influence on excess returns over time, represents an important oversight. Our research extends the existing research by exploring the importance of accounting for how low-risk portfolios evolve dynamically over time and how exposure to size, style, and momentum contribute to this performance.

Using CAPM beta as our measure of risk, we first update earlier findings through 2012 confirming previously reported evidence on the existence of the low-risk anomaly on a sample of U.S. large cap stock returns.[3] We next calculate the time-varying valuation (using book-to-price) of low-volatility portfolios and demonstrate how this valuation at any point in time relates to the future performance of low-risk portfolios in our sample. Here, we document the presence of secular

[3] We find similar results when we use IVOL as our risk measure but do not report results due to space constraints.

environments in which, consistent with theory, high-risk stocks tend to outperform low risk stocks for extended periods. We then expand this analysis by demonstrating that value and momentum characteristics represent an important influence on low-risk portfolio performance. Here, we find that low-risk portfolio exposures to value and momentum tend to cycle through time, which suggests that it is important to understand how valuation and price momentum act as drivers of low-risk stock portfolios.

**Data**

We obtain stock return data from the Center for Research in Security Prices (CRSP) for all stocks trading on NYSE, AMEX, and Nasdaq for 1925 through 2012. However, our analysis will primarily focus on the 1968-2012 period following the existing literature. We review the evidence for the longer period at the end of the paper. We focus on common stocks only (share code 10 and 11). For delisted firms, we fetch the returns in the delisting month from CRSP. However, if the delisting is for performance-related reasons, we set the delisting return equal to -55% if trading on Nasdaq or -30% if on NYSE/Amex (see analysis of CRSP delisting bias in Shumway (1997) and Shumway and Warther (1999)). To minimize the impact of illiquid stocks, we exclude stocks with prices lower than $2 or greater than $1,000. Following Baker et al (2011), we focus on large-cap stocks, defined as those firms in the top one-third based on market capitalization using NYSE breakpoints. We focus on large-cap stocks because implementing a low-risk strategy requires frequent rebalancing [Li, Sullivan, and Garcia-Feijoo (2014)] and as such, the efficacy of implementation within the very small cap stock universe is questionable. Here, we further note (and confirm empirically), as consistent with this previous research, that outperformance of low-risk stocks in the large-cap universe is diminished versus their small-cap counterparts over the sample period.

We obtain accounting data from Compustat. We use information reported as of December of each fiscal year (i.e., we only use firms with a December fiscal year-end) and follow Fama and French (1992) in the computation of book equity. To minimize the impact of newly listed firms, we require two years of data for a company to be included in the sample. For periods prior to 1951, we obtain data from Ken French's website.

**Model and Analysis**

As mentioned, we report results for large market capitalization stocks only, using the top one third of companies based on NYSE breakpoints. Each month, we sort stocks into quintiles based on risk, where risk is measured by beta ($b_i$) as estimated from the CAPM market model shown in equation 1 [Bradley, Baker, and, Wurgler (2011)]:

$$R_{i,t} - R_{f,t} = a_i + b_i\,(R_{M,t} - R_{f,t}) + \varepsilon_{i,t} \qquad (1)$$

Beta is estimated monthly in regressions of excess returns on the CRSP value-weighted index over the prior 60 months (minimum of 24 months). Specifically, for each month t, we estimate beta for each stock using the prior 60 months of returns, to include month t. We sort stocks into risk quintiles based on the estimated beta and compute value-weighted average returns for each quintile in month t+1. The average of the monthly value-weighted stock returns by risk quintile is reported in Table 1. We calculate the arithmetic and geometric average returns for the quintile portfolios over the sample period.

In Table 1, column 2 we report the value-weighted average monthly raw returns (e.g., not excess returns) on quintile risk portfolios using beta as our measure of risk. Consistent with previous literature, we find that stocks in the lowest beta quintile outperform those in the highest quintile over the sample period for both arithmetic average and geometric average returns. For example, the average arithmetic return on the lowest quintile is 0.89% over the 1968-2012 period, whereas the average arithmetic return on the highest quintile is 0.73%.

We further note that although the average betas rise meaningfully for each successively higher quintile, average returns for the first four beta quintiles are all roughly equivalent for both arithmetic and geometric means, respectively. The average returns associated with the highest beta quintile then decline, with arithmetic means falling from roughly 0.90% per month in the lower quintiles to 0.73% per month in the highest quintile, and geometric returns similarly falling from about 0.80% to 0.47% per month. Importantly for investors, as can also be observed from Table 1, corresponding Sharpe ratios successively decline with increasing risk quintile portfolios with Sharpe ratios falling meaningfully from 0.45 in the lowest risk to 0.15 in highest risk quintile portfolio. Thus, a low volatility portfolio historically has offered a compelling risk adjusted return three times higher than that of a high-risk portfolio.

Figure 1 considers geometric returns of risk quintile portfolios by plotting the cumulative growth of $1 as invested in each quintile portfolio over the sample period. Consistent with the findings of Baker, Bradley, and Wurgler (2011), geometric returns for high beta stocks underperform that of low beta stocks with the lowest four beta quintiles performing somewhat closely together versus the highest beta quintile.[4]

The related literature typically examines the performance of a zero-cost strategy that goes long the stocks in one of the extreme quintiles and short the stocks in the opposite extreme quintile (e.g., Ang, Hodrick, Xing, and Zhang, 2009). As reported in Table 1, the raw return on the zero-cost spread portfolio that goes long the lowest-risk quintile and short the highest-risk quintile is 0.16% but insignificantly different from zero at the 5% level (the t-statistic is 0.63)[5]. The Sharpe ratio is 0.10.[6] This

[4] So-called "volatility drag" creates a headwind likely contributing to the underperformance of higher risk quintiles over time. As is well known, the geometric return compounds at a rate roughly equivalent to the arithmetic return minus one-half of the variance of returns.

[5] We do not claim that the data follow a Gaussian distribution, but we nonetheless follow the extant literature in interpreting *t* statistics in this manner. The well-known caveats to such an interpretation apply.

suggests that any outperformance of a risk-based zero-cost spread portfolio is not economically meaningful over time, on average, for the large cap universe of stocks.[7] This finding is consistent with Clarke, De Silva, and Thorley (2014) who employed a "VMS" (volatile minus stable) factor.

In Figure 2, we see that the zero-cost long-short portfolio generates a cumulative return of roughly zero over our sample period thus underperforms the market. Therefore, a zero-cost arbitrage portfolio that is long low risk and short high risk stocks performs relatively poorly, on average over time [Li, Sullivan, and Garcia-Feijoo (2013)].

However, a potential concern with the zero-cost long-short portfolio, which equally dollar weights the long side and the short side, is that this portfolio– in our case– results in a negative portfolio beta over the sample period, an undesirable trait for most investors who do not ordinarily seek to have a persistently net short position to the equity market over time. In response, we consider an alternative approach to constructing a long-short low risk portfolio that is instead roughly beta neutral (beta of zero), on average over time [Frazzini and Pedersen (2014)].[8] In contrast to our zero-cost long-short portfolio, which is 100% long the low-risk quintile and 100% short the high-risk quintile, our beta-neutral portfolio is formed by going long 100% the lowest-risk stocks while shorting only 25% of the highest risk quintile over the sample period. Such a beta-neutral portfolio would, of course, possess far less (if any) market risk over time and thus offers a more practical approach to capture the observed risk related anomalous returns.

To compare the two long-short portfolio betas, from Table 1, we calculate that our zero-cost long-short portfolio has an average market related beta of -1.29, calculated as 1.0*0.47 –1.0* 1.76 = -

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[6] For Table 1, we report raw returns ignoring any return from short cash proceeds associated with our long-short portfolios. However, we appropriately use excess returns in reporting all Sharpe ratios.

[7] For more on the efficacy of extracting the low-volatility anomalous returns, see Li, Sullivan, and Garcia-Feijoo (2014) who provide a detailed look to include various time periods, market capitalization groupings, and weighting schemes.

[8] Our approach is much simpler than that of Frazzini and Pedersen's (2014) betting-against-beta (BAB) strategy which is dynamically managed to keep the portfolio at roughly a zero beta. A BAB portfolio holds low-beta assets, leveraged to a beta of one, and shorts high-beta assets, de-leveraged to a beta of one.

1.29, while our beta neutral portfolio has an average market beta of about zero, or 1.0*0.47 – 0.25*1.76 = 0.03. From Figure 2, we see that our beta-neutral long-short portfolio meaningfully improves performance versus our zero-cost long-short portfolio over the study period. That the beta-neutral portfolio underperforms the market portfolio over the study period is not a surprise given that it is zero beta.

Table 1 shows highly statistically significant average returns of 0.71% per month for the beta-neutral portfolio over the sample period versus the statistically insignificant average arithmetic returns of 0.16% for the zero-cost long-short portfolio. The resulting Sharpe ratio of 0.45 for the beta-neutral long-short portfolio is also much improved over the Sharpe ratio of 0.10 for the zero-cost long-short portfolio, and roughly equivalent to the Sharpe ratio for the lowest risk quintile portfolio. For comparison purposes, the average arithmetic return on the market (i.e., the CRSP value-weighted index) is 0.87% with a Sharpe ratio of 0.33.

To summarize, we find little relationship between risk and returns for the four lowest risk quintiles, but do observe a marked underperformance for the highest risk quintile versus its lower risk quintile counterparts. Sharpe ratios decline meaningfully as portfolio risk rises leading to declining returns per unit of risk. In an attempt to arbitrage the lower relative returns of the high-risk quintile versus the lowest risk quintile, we further observe no outperformance for a zero-cost long-short portfolio in either an arithmetic or geometric return basis. However, our alternative long-short beta-neutral portfolio demonstrates much stronger performance over time with a Sharpe ratio in line with that of the lowest risk quintile and higher than that of the market portfolio over the sample period.

The results reported thus far, however, conceal secular environments in which, as we will show, high risk stocks tend to *outperform* low risk stocks for extended periods, consistent with theory. As we will discuss, our evidence suggests that these periods of high-risk stock outperformance correspond to initial relative undervaluation of those high-risk stocks. We now turn attention exploring this time-varying performance in more detail.

**Low-Risk and Valuation**

We now examine the relative valuation levels of the lowest and highest risk quintile portfolios over time using the average book-to-price ratio, B/P, for each of the two portfolios, each month. Our chosen valuation measure, B/P, is defined as the book value of common equity, divided by market value of equity. Book equity is computed as in Fama and French (1992) using information from the prior fiscal year. Market capitalization is computed at the end of each month [Asness and Frazzini (2013)] as share price times the number of shares outstanding.

Specifically, as discussed earlier, for each month t, we estimate beta for each stock using the prior 60 months of returns. We then sort stocks into risk quintiles based on the estimated beta and compute value-weighted average returns for each quintile in month t+1. For valuation purposes, we then calculate our B/P ratio for each stock for each month t. This allows us to compute the mean B/P for the portfolio of stocks in the lowest risk quintile, and for the portfolio of stocks in the highest risk quintile, each month. We also subtract the average B/P of the high beta quintile from the low beta quintile and denote the difference as "B/P spread." We have one value per month of B/P for each risk quintile and for the B/P spread over the sample period.

We begin our exploration of the interaction of valuation and momentum in low-risk portfolios by visual inspection. In Figure 3, we plot the time varying mean level of B/P for the market portfolio and also for the large cap universe the B/P for those stocks in the lowest and highest beta quintiles and also the B/P spread. The shaded areas correspond to NBER recession periods. Two observations stand out. First, high beta B/P ratios tend to “spike” during recessions compressing the spread between low and high beta B/P ratios sometimes to the point of reversing the typical relationship. That is, B/P ratios for high risk stocks are typically lower than B/P ratios for low-risk stocks (i.e., the B/P spread is positive) indicating a valuation premium for high-risk stocks. However, during recessionary periods, perhaps as result of a “flight to safety,” the prices of high beta stocks decline significantly and the B/P spread falls. Often during such periods the valuation spread even becomes negative such that high beta stocks are trading at a relative discount to low beta stocks, based on B/P.

Second, following recessions, the B/P spread tends to increase dramatically perhaps as investors increase risk appetites and the valuation of high-risk stocks reverts to more normal levels. Incidentally, we note that the spread moved to a negative value during the 2008 global financial crisis, but interestingly had not reverted to more normal levels by the end of our study period, 2012. Instead, after having initially bounced from a 30 year low since the reccession of 1974-1975, the B/P spread moved back down to its 2008 crisis lows indicating a continued deep relative valuation discount for high-risk stocks. Only time will tell whether the B/P spread will revert back to more normal levels.

We now turn attention to a more formal empirical analysis of the relationship between low-risk portfolio performance and the well-known value and momentum factors. Here, we first compare the relative performance in month t+1 of low-risk and high-risk stocks in accordance with varying initial (time t) levels of B/P for those stocks. To accomplish this, we employ the approach described earlier whereby we form risk quintile portfolios and then calculate the B/P spread each month by subtracting the average B/P of the high beta quintile from the low beta quintile. We then create B/P spread quintiles by rank ordering the monthly B/P spread. Data are for the period 1968-2012. We delete the top and bottom 0.5% of the B/P observations to minimize the impact of extreme observations.

In Table 2, Panel A, we report statistics similar to those in Table 1, but now separate the long-short risk spread portfolio into B/P spread quintiles. Importantly, this approach allows us to identify months in which the B/P spread is low and months in which the spread is high for the long-short risk portfolio. In this way, we can examine the future excess return performance of the zero-cost and beta-neutral spread portfolios relative to their initial valuations as based on the B/P spread quintiles.

Table 2, Panel A reports value-weighted average returns in month t+1 on beta quintile portfolios separated according to B/P spread in month t.[9] Our stock portfolios are rebalanced monthly in accordance with the risk quintiles discussed above.[10] Focusing first on the highest B/P spread portfolios (when low beta stocks begin in month t at a valuation discount relative to high beta stocks) we see that low beta stocks meaningfully outperform high beta stocks on average in the next month over the sample period. More specifically, as shown in the bottom row of Table 2 Panel A (when low beta stocks are at the deepest valuation discount relative to high beta stocks), the average one-month ahead return on the beta quintiles range from 1.42% for the lowest to 0.55% for the highest risk quintile. For this B/P spread quintile, the zero-cost spread portfolio average return is a positive 0.87%, though statistically insignificant (the t-stat is 1.46). However, in contrast, as can be seen from the first row of Table 2 Panel A, when the B/P spread is the most negative, that is, when initial valuation levels in month t reflect the greatest relative valuation discount for high risk stocks, the high beta quintile instead tends to outperform the low beta quintile in the next month. The average return is 0.13% for the lowest and 0.35% for the highest risk quintile. The accompanying average return on the zero-cost spread portfolio over the sample period is -0.21%, though statistically insignificantly different from zero (the t-stat is -0.35). Results for our beta neutral portfolio are similar, though slightly improved, to our zero-cost long-

[9] We report excess returns for both of our long-short portfolios. For the regular long-short portfolio, we start with a portfolio that is 100% long and 100% short. The return on this portfolio equals (100% x Long portfolio return - 100% x Short portfolio return + 100% x Cash return on short proceeds). This makes the excess portfolio return, or the portfolio return in excess of the return on 3-month T-Bills, equal to 100% x (Long Portfolio Return - Short Portfolio Return). Given that our beta neutral portfolio is 100% long and 25% short, the return on this portfolio equals (100% x Long portfolio Return - 25% x Short portfolio return + 25%x Cash return on short proceeds) with excess returns on the beta neutral portfolio equal to (100% x Long portfolio return - 25%x Short portfolio return - 75%x Cash return).

[10] We rebalance monthly consistent with the extant literature that purports a low-risk alpha associated with a monthly rebalancing process. We use the term "investment horizon" and not "holding period" as we are rebalancing our quintile risk portfolios each month based on the level of beta for each stock instead of simply buying and holding that portfolio. We believe this process better reflects the practice of portfolio construction.

short portfolio. None of the zero-cost long-short portfolio average returns are statistically different from zero while the beta neutral portfolio returns are significant on two occasions (in the two highest B/P spread quintiles, or when low-beta stocks have low relative initial valuations).

In Table 2, Panel B, we extend the evidence from Panel A by reporting annualized returns of our two long-short spread portfolios over longer future (t+n) investment horizons, again rebalanced monthly. The main difference is that we now extend our reported results from a one-month (t+ 1) horizon to include cumulative returns for various future investment horizons up to five years (t+ 60). We note that results are reported for overlapping periods, so the usual caveats apply in interpreting the results. Here again, we find that there is an interaction between the performance of rebalanced low-risk minus high-risk portfolios and initial valuation levels. That is, a portfolio of high-risk stocks outperforms a portfolio of low-risk stocks from one year (t+12) to five years (t+60) following periods that begin with a negative B/P spread generating negative returns for the zero-cost low-high risk portfolio. Specifically, average annual cumulative returns are -5.80% in t+12, and around -2.83% for five years (t+60) following initial valuation month, *t*. As mentioned, a negative B/P spread (computed as low-beta minus high-beta) suggests high-beta stocks are selling at a discount at the time of portfolio formation in initial month t. By contrast, low-risk stocks tend to outperform when the B/P spread is high at time of portfolio formation, or when low-risk stocks begin the period at a relative discount as shown in the bottom row of Table 2 Panel B.

In Table 2, Panel C, we see that the beta-neutral portfolio, by reducing the weighting to the high risk quintile to 25%, improves overall portfolio performance over each of the investment horizon periods versus the regular long-short portfolio which has an equal 100% weighting to both the high and low risk quintiles. Consistent with expectations, the beta-neutral portfolio returns generally increase with improved valuation of the low-risk stocks at the time of portfolio formation. Interestingly, unlike the zero-cost risk portfolio, the beta neutral portfolio experiences no negative returns for any holding period, no matter the starting valuation.

Though the above findings are new, the overall evidence from Table 2 should come as no surprise– after all, finance theory strongly supports the notion that valuation matters. As demonstrated by the zero-cost low-high risk portfolio returns, the lowest quintile risk portfolio outperforms the highest risk portfolio only when valuation is strongly in its favor. Specifically, only when low risk stocks are at their most attractive valuation levels relative to high-risk stocks (shown by the highest B/P spread quintile in the bottom row of Table 2, Panel B), do low risk stocks consistently outperform high risk stocks across all portfolio investment horizon periods. The remaining valuation quintiles report a mix of positive and negative spread returns for the zero-cost low-high risk spread portfolios across the various investment horizons. The practical implication of our results is the possibility that the performance of low-risk strategies is influenced by time-varying valuation premia. To be clear, we are not suggesting that timing of these premia should be attempted or that it can be accomplished. Our analysis is of course, ex-post. The ex-ante analysis is an entirely different matter which we leave to future research efforts.

These results suggest that risk-based portfolios may have important time-variation in their exposure to well-known characteristics influencing stock returns. We take this idea and now build on the evidence from Table 2 with a more formal analysis. In Table 3, we report monthly alpha results and t-statistics based on the intercept from regressions of our two low-high portfolio spread excess returns on the market (Panel A), and on the well-known four factors of Fama and French (1993) and Jegadeesh and Titman (1993): the market, SMB, HML, and MOM (Panel B). As noted, for example, by Novy-Marx (2012), the regression intercept's t-statistic is the information ratio of the low-high risk strategy benchmarked to the strategies embodied by the explanatory variables (i.e., the market in Panel A and size, value and momentum in Panel B). A statistically significant intercept indicates that inclusion of the low-risk strategy can result in an information ratio improvement over one that can be achieved by employing the strategies embodied by the explanatory variables alone. By contrast, an insignificant intercept indicates there may be no benefit to the portfolio strategy in terms of information ratio improvement in adding the low-risk strategy versus a strategy employing the market, size, value, and momentum alone. However, we emphasize that we do not seek to "enhance" existing low-risk strategies. Rather, our aim is to better understand the dynamic interactions between low-risk portfolios, and characteristics such as style and momentum.[11]

As before, we estimate beta for each stock using the prior 60 months of returns and sort stocks into risk quintiles based on their estimated beta. Portfolios are rebalanced each month t, and average returns are computed each month t+1. We then run regressions of excess returns on the low-volatility strategy against systematic risk factors using overlapping sets of 12, 24, etc. months. Then, we report the average of the estimated alphas (Table 3) and slope coefficients (Table 4). For example, for the t+12 results shown in column 4, Table 3 Panel A, we run regressions of the beta spread quintile excess returns on the market risk premium (MKT) using the months of January 1968 thru December 1968, February 1968 thru January 1969, March 1968 thru February 1969 etc. (when December 1967, January 1968, and February 1968, respectively, are in the same B/P quintile). Given our use of overlapping periods, in reporting t-statistics we attempt to correct for autocorrelation and heteroskedasticity using Newey-West (1987), although the reliability of the t-statistics are nonetheless likely still weakened.

In Table 3, Panel A, we find that unconditional alphas for both types of our long-short portfolios tend to be insignificantly different from zero when the B/P spread is within the lowest three quintiles (i.e., when low risk stocks tend to be at a valuation premium to high risk stocks). However, when the

[11] Clarke, De Silva, and Thorley (2010) use the Fama and French (1993) methodology to create a volatility factor. They report the volatility factor is an important risk factor, though it is correlated with MKT and SMB. Based on their analysis, the relationship between the volatility factor and HML is not stable and has turned negative in recent decades. Our findings extend and clarify theirs, particularly regarding the interactions between low-risk strategies, and HML and UMD.

B/P spread is within its highest two valuation quintiles (i.e., when high risk stocks are trading at a premium), alphas tend to be significantly positive for our two long-short portfolios for up to five years after portfolio formation. Furthermore, alphas in the highest two B/P spread quintile are significantly positive, as shown by corresponding t-statistics.

Our investigation of the connection between strategies based on style and momentum, and the low-volatility strategies begins with Table 3, Panel B whereby we repeat the regression analysis from Panel A, but now conditionally include the four factors of MKT, HML, SMB, and MOM. In comparing Table 3, Panel A against Panel B, when the B/P spread is within its highest two valuation quintiles (i.e., when high risk stocks are trading at a premium), we observe a decline in the conditional alphas and t-statistics on the low-volatility strategy once the additional factors are included in the regressions. That is, the mostly significant alphas found in the bottom two rows of Panel A are now diminished and only occasionally significant for both of our long-short portfolio strategies. This suggests that there exists an important association between the valuation and performance of portfolios formed on beta, and strategies based on value and momentum (recall that the smallest stocks are excluded from the sample). Importantly, the lower alphas and t-statistics indicate that portfolio performance and information ratios tend to degrade once value and momentum strategies are included along with the low-risk strategy. This is an important finding for practitioners in implementing low-risk strategies. It means that an interaction among low-risk, value and momentum exists historically that imparts an influence on portfolio performance. Results for the beta-neutral strategy, also reported in Table 3, confirm the evidence from the original low beta strategy.

Taken together, the results from Table 3, Panel A and Panel B reinforce and extend the evidence from Table 2. Firstly, future performance of a low-risk trading strategy depends importantly on the initial price paid. In other words, extracting excess returns from the low-volatility anomaly depends importantly on initial valuation levels– low-risk stocks tend to outperform over future investment horizons, but only when initial valuations are in their favor. This finding highlights the connection between low-risk and value-based strategies. Additionally, once the well-known cross sectional factors of style and momentum are controlled for, alphas and information ratios for our two long-short portfolio strategies decline. This finding indicates there are important interactions among strategies based on these factors. We investigate this issue in more detail next.

**Interaction of Low-Risk, Value, and Momentum**

We now extend our analysis by further exploring the dynamic interactions of our two long-short portfolio strategies with value and momentum. In Table 4, we explore the role of the value and momentum factors in explaining the risk exposure and performance of the low-high risk spread portfolio over time. Here, we apply the same estimation procedure as used for Table 3, but we now report average exposures (i.e., slopes) on the HML and MOM factors over various forward-looking investment horizons. Table 4, Panel A, shows that beta spread portfolio returns tend to exhibit low levels of exposure relative to HML when the initial B/P spread is negative (i.e., when low risk stocks begin the period at a valuation premium), but exposures on HML rise when the initial B/P spread is positive (i.e. when high risk stocks trade at a premium). This is not surprising, as B/P and HML are directly connected in that B/P is the firm characteristic that is used to determine the level of the HML factor and low risk stocks outperform when their B/P is higher relative to their high-risk counterparts (highest B/P spread quintile).

Of greater interest is the evidence from Table 4 Panel B on momentum. Following portfolio formation, the beta spread strategy tends to exhibit higher exposure on MOM when the B/P spread begins the period in positive territory (i.e., when initial valuation levels favor low-risk stocks). This finding suggests that the performance of low-beta strategies is also influenced by the momentum factor.

The combination of initial valuation levels and momentum sheds new light on the performance of low-risk strategies.

To aid understanding of our findings regarding the importance of style and momentum on low-risk portfolio performance, Figure 4 graphically plots the rolling four-year correlations between the return to the risk spread portfolio and the value (HML) and momentum (MOM) factors all calculated as described earlier. Consistent with our earlier findings, the risk spread portfolio has historically shown meaningful cyclical exposure to both a value factor and a momentum factor. Interestingly, the value and momentum factor exposures appear diversifying in that they present a tendency to move in opposite directions from each other over time (Asness 1997). It is interesting to further note that in the most recent years of our sample period, exposure of the risk spread portfolio to the value factor approached all-time lows while the opposite was true for the momentum factor which was nearing all-time highs. That is, as of the end of 2012, the relationship of the low risk portfolio to the value factor was very strongly negative but strongly positive for the momentum factor. For the value factor, this change represents a complete reversal from its strong positive relationship since the 1980s up until the recent financial crisis. Regarding MOM, the correlation with the zero cost risk spread portfolio tends to decrease, often becoming negative, around recessionary periods as can be seen by the negative correlations around 2001 and more recently in 2008. The correlation of the low-risk portfolio to momentum tends to move higher during expansionary periods, as has been the case since 2008. This makes intuitive sense given the infrequent but severe losses of momentum stocks (e.g., Daniel 2011). Together, these findings highlight the link between valuation levels, the performance of low-risk portfolios, and momentum. Only time will tell whether these recent trends in correlations observed between the low-high risk spread portfolio and the MOM and HML factors will revert to more typical levels or continue their respective march in opposite directions.

## The Longer Evidence

Given the observed relationship between low-high risk spread portfolio performance and economic recession periods, it seems important to attempt to explore these relationships during earlier recessions, especially the Great Depression era. With that motivation, we now extend the analysis to the beginning of the previous century, for a total of 85 years. We note that the data prior to 1968 may be less reliable due to possible survivorship bias although still useful for comparison purposes. As shown in Figure 5, consistent with our earlier findings, the B/P ratio for high-risk large cap stocks increases dramatically during turbulent economic times– high-risk stocks become relatively much cheaper. In Table 5, we follow the procedure used in Table 2. The main difference being that we now report results over a much longer 1930-2012 period (the data period begins in 1925 with the first five years of data used for estimation). Consistent with our earlier findings, the lowest-risk stock portfolio outperforms the highest-risk stock portfolio over various investment horizons only when the period begins in the quintile of highest B/P spreads (low risk initiates the period at a B/P discount).

## Discussion and Conclusions

Prior research on the low-volatility "anomaly" has focused on cross-sectional evidence emphasizing that low-volatility stocks outperform high-volatility stocks. We extend this research by examining the time-varying performance and influence of well-known investment factors on the low-risk strategy to include a beta-neutral low-risk strategy of practical relevance. We do so primarily by: reporting a strong dynamic link between the performance of low-volatility strategies and initial valuations, investigating the performance of both zero-cost and a beta-neutral low-volatility strategy, and reporting an important connection between the strategy and economic activity and also momentum.

In putting together our resulting research findings, the picture that emerges is the following. The performance of low-risk strategies is time-varying and depends on initial valuation (like any other strategy) and low-risk strategy performance appears to be related to the well-known style and momentum factors. In other words, low-risk stocks tend to outperform high-risk stocks, but are most likely to do so when initial valuation levels favors low-risk stocks. Thus, investment success seems to depend importantly on the price paid. Additionally, once the well-known cross sectional factors of style and momentum are controlled for, alphas and information ratios for our two long-short portfolio strategies decline.

We have shown that there have been extended periods of time over the last 85 years during which high-risk stocks cumulatively outperform low-risk stocks. These periods tend to have coincided to some degree with economic cycles. Put differently, low-risk strategies historically outperformed more reliably when implemented when low-beta stocks exhibited relatively high B/P levels, and even more so if they subsequently load positively on momentum. Although, interestingly, our beta neutral portfolio experiences no negative returns for any holding period, no matter the starting valuation.

Taken together, we find that low-risk investing does indeed have worth, but investors should additionally consider how valuation and momentum interact with low-risk portfolio performance over time. Although one should be wary of making predictions based on past events, our findings suggest the performance (like any quantitative investment strategy) of low-beta stocks relative to high-risk stocks relates importantly to macroeconomic, market and valuation factors. The historical differences in performance of our two low-risk portfolio strategies also suggests the importance of careful portfolio construction. The practical implication of our results is an indication that the performance of low-risk strategies is influenced by the approach to constructing the low-risk portfolio strategy and by time-varying exposure to the market environment and valuation premia. Investors can benefit from a fuller understanding of how these factors may influence future performance of low-risk portfolio strategies.

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**Table 1**

**Risk and Return Characteristics of Beta Portfolios (1968-2012)**

| *Beta Quintile* | VWRet (%) (arithmetic mean) | VWRet (%) (geometric mean) | Beta | Sharpe Ratio |
|---|---|---|---|---|
| Low | 0.89% | 0.83% | 0.47 | 0.45 |
| 2 | 0.92% | 0.84% | 0.76 | 0.42 |
| 3 | 0.86% | 0.75% | 0.98 | 0.32 |
| 4 | 0.85% | 0.70% | 1.24 | 0.27 |
| High | 0.73% | 0.47% | 1.76 | 0.15 |
| Low-High | 0.16% (0.63) | -0.02% | -1.29 | 0.10 |
| Beta Neutral | 0.71%*** (5.49) | 0.67% | 0.03 | 0.46 |
| Market | 0.87%*** (4.35) | 0.76% | 1.00 | 0.33 |

Table 1 reports raw return and risk and characteristics by Beta quintiles over the period 1968-2012 (540 months). The sample includes large-cap stocks only (largest one-third using NYSE breakpoints). Arithmetic mean is the average value-weighted monthly raw return. Beta is computed monthly in regression of excess returns on the CRSP value-weighted index over the previous 60 months. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Numbers within parenthesis are t-statistics.

**Table 2**
**Returns on Beta risk portfolios by B/P spread (1968-2012)**
**Panel A**

| B/P Spread Quintiles (B/P for low beta stocks– B/P for high beta stocks) | | | | Average VW return in month t+1 | | | | | Low Beta - High Beta | Beta Neutral |
|---|---|---|---|---|---|---|---|---|---|---|
| **Quintile** | **From** | **To** | **Avg monthly # stocks** | **Low Beta** | **2** | **3** | **4** | **High Beta** | **Avg Ret (t-stat)** | **Avg Ret (t-stat)** |
| Low | -0.55 | -0.01 | 104 | 0.13% | 0.50% | 0.41% | 0.39% | 0.35% | -0.21% (-0.35) | -0.12% (-0.42) |
| 2 | -0.01 | 0.12 | 101 | 1.22% | 1.40% | 1.31% | 1.34% | 1.01% | 0.21% (0.37) | 0.69% (2.83) |
| 3 | 0.12 | 0.22 | 108 | 0.90% | 0.96% | 1.28% | 1.38% | 1.30% | -0.40% (-0.63) | 0.21% (0.66) |
| 4 | 0.22 | 0.27 | 106 | 1.01% | 1.08% | 0.94% | 0.87% | 0.77% | 0.23% (0.51) | 0.47%* (1.79) |
| High | 0.27 | 0.59 | 94 | 1.42% | 0.99% | 0.71% | 0.65% | 0.55% | 0.87% (1.46) | 0.80%** (2.50) |

**Table 2**

**Panel B**

| **B/P Spread Quintiles (B/P for low beta stocks– B/P for high beta stocks)** | | | **Annualized Future Cumulative Return on Low Beta-High Beta Strategy** | | | | |
|---|---|---|---|---|---|---|---|
| **Quintile** | **From** | **To** | t+12 | t+24 | t+36 | t+48 | t+60 |
| Low | -0.55 | -0.01 | -5.80% | -3.63% | -3.37% | -3.29% | -2.83% |
| 2 | -0.01 | 0.12 | 4.64% | -0.67% | 0.24% | 0.33% | 0.24% |
| 3 | 0.12 | 0.22 | -6.84% | -5.30% | -3.99% | -2.50% | -2.23% |
| 4 | 0.22 | 0.27 | 3.36% | 1.62% | -2.45% | -3.11% | -2.81% |
| High | 0.27 | 0.59 | 12.52% | 8.45% | 6.45% | 4.96% | 4.40% |

**Panel C**

| **B/P Spread Quintiles (B/P for low beta stocks– B/P for high beta stocks)** | | | **Annualized Future Cumulative Excess Return on Beta Neutral Strategy** | | | | |
|---|---|---|---|---|---|---|---|
| **Quintile** | **From** | **To** | t+12 | t+24 | t+36 | t+48 | t+60 |
| Low | -0.55 | -0.01 | 2.30% | 3.71% | 3.06% | 1.04% | 1.62% |
| 2 | -0.01 | 0.12 | 3.97% | 1.51% | 2.06% | 2.47% | 2.61% |
| 3 | 0.12 | 0.22 | 2.53% | 2.28% | 3.31% | 3.74% | 3.49% |
| 4 | 0.22 | 0.27 | 5.63% | 4.73% | 4.09% | 4.35% | 4.34% |
| High | 0.27 | 0.59 | 10.27% | 10.42% | 9.25% | 8.99% | 9.10% |

We examine the excess returns for our two risk-based quintile spread portfolios across the quintile valuation-based B/P spread quintile portfolios. See text for fuller description. In Panel A, Newey-West (1987) t-statistics are shown within parentheses. The sample includes a total of 540 months, or 540 observations of the B/P spread, so each row is based on 108 months. "Avg monthly # stocks" is the average number of stocks in the Long top quintile and Short bottom quintile portfolios (the number of stocks in the long and short portfolios are the same) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

**Table 3**
**Risk-Adjusted Returns on Beta spread portfolios by B/P spread (1968-2012)**
**Panel A**

| **B/P Spread Quintiles (B/P for low beta stocks– B/P for high beta stocks)** | | | **Monthly Regressions of Low Beta-High Beta Strategy against Market** | | | | |
|---|---|---|---|---|---|---|---|
| | | | **Estimated alpha (t-statistic)** | | | | |
| **Quintile** | **From** | **to** | t+12 | t+24 | t+36 | t+48 | t+60 |
| Low | -0.55 | -0.01 | 0.07% (0.10) | 0.38% (0.50) | 0.30% (0.73) | 0.08% (0.43) | 0.14% (1.15) |
| 2 | -0.01 | 0.12 | 0.45% (0.90) | 0.21% (0.26) | 0.37% (1.02) | 0.37% (1.53) | 0.36% (1.23) |
| 3 | 0.12 | 0.22 | -0.11% (-0.34) | 0.03% (0.11) | 0.23% (1.04) | 0.33%* (1.73) | 0.37%** (2.25) |
| 4 | 0.22 | 0.27 | 0.46%*** (2.62) | 0.35%** (2.30) | 0.25% (1.64) | 0.32%* (1.68) | 0.39%*** (2.69) |
| High | 0.27 | 0.59 | 1.04%*** (5.11) | 1.02%*** (3.76) | 0.90%** (2.02) | 0.92%*** (3.11) | 0.92%*** (4.28) |

| **B/P Spread Quintiles (B/P for low beta stocks– B/P for high beta stocks)** | | | **Monthly Regressions of Beta Neutral Strategy against Market** | | | | |
|---|---|---|---|---|---|---|---|
| | | | **Estimated alpha (t-statistic)** | | | | |
| **Quintile** | **From** | **to** | t+12 | t+24 | t+36 | t+48 | t+60 |
| Low | -0.55 | -0.01 | 0.00% (-0.01) | 0.16% (0.38) | 0.12% (0.42) | -0.01% (0.12) | 0.02% (0.18) |
| 2 | -0.01 | 0.12 | 0.15% (0.44) | 0.06% (0.13) | 0.15% (0.68) | 0.15% (0.89) | 0.15% (0.67) |
| 3 | 0.12 | 0.22 | -0.09% (-0.51) | 0.03% (0.20) | 0.14% (1.21) | 0.20%* (1.74) | 0.21%** (2.07) |
| 4 | 0.22 | 0.27 | 0.27%** (2.56) | 0.16%** (1.98) | 0.10% (1.11) | 0.17%* (1.68) | 0.23%*** (2.91) |
| High | 0.27 | 0.59 | 0.68%*** (5.09) | 0.63%*** (4.47) | 0.54%** (2.47) | 0.52%*** (3.29) | 0.52%*** (4.07) |

**Table 3**
**Panel B**

| **B/P Spread Quintiles (B/P for low beta stocks– B/P for high beta stocks)** | | | **Regressions of Low Beta-High Beta Strategy against FF4 Factor Model** | | | | |
|---|---|---|---|---|---|---|---|
| | | | **Estimated alpha (t-stat)** | | | | |
| **Quintile** | **From** | **To** | t+12 | t+24 | t+36 | t+48 | t+60 |
| Low | -0.55 | -0.01 | 0.10%<br>(0.31) | 0.36%<br>(1.48) | 0.37%<br>(1.22) | 0.18%<br>(0.71) | 0.22%<br>(1.30) |
| 2 | -0.01 | 0.12 | 0.18%<br>(0.66) | -0.04%<br>(-0.18) | 0.04%<br>(0.30) | 0.15%<br>(1.04) | 0.15%<br>(0.72) |
| 3 | 0.12 | 0.22 | 0.03%<br>(0.16) | -0.07%<br>(-0.50) | -0.06%<br>(-0.38) | -0.10%<br>(-0.42) | -0.11%<br>(-0.67) |
| 4 | 0.22 | 0.27 | 0.06%<br>(0.24) | -0.12%<br>(-0.69) | -0.10%<br>(-0.62) | -0.03%<br>(-0.20) | -0.09%<br>(-0.58) |
| High | 0.27 | 0.59 | 0.40%*<br>(1.86) | 0.40%**<br>(2.19) | 0.27%<br>(1.06) | 0.30%<br>(1.28) | 0.29%*<br>(1.72) |

| **B/P Spread Quintiles (B/P for low beta stocks– B/P for high beta stocks)** | | | **Regressions of Beta Neutral Strategy against FF4 Factor Model** | | | | |
|---|---|---|---|---|---|---|---|
| | | | **Estimated alpha (t-stat)** | | | | |
| **Quintile** | **From** | **To** | t+12 | t+24 | t+36 | t+48 | t+60 |
| Low | -0.55 | -0.01 | 0.03%<br>(0.19) | 0.18%<br>(1.35) | 0.19%<br>(1.00) | 0.10%<br>(0.58) | 0.11%<br>(0.91) |
| 2 | -0.01 | 0.12 | 0.04%<br>(0.20) | -0.02%<br>(-0.17) | 0.01%<br>(0.13) | 0.06%<br>(0.56) | 0.06%<br>(0.39) |
| 3 | 0.12 | 0.22 | -0.01%<br>(-0.07) | -0.03%<br>(-0.28) | -0.02%<br>(-0.20) | -0.05%<br>(-0.37) | -0.07%<br>(-0.64) |
| 4 | 0.22 | 0.27 | 0.06%<br>(0.29) | -0.14%<br>(-1.13) | -0.11%<br>(-0.95) | -0.04%<br>(-0.34) | -0.06%<br>(-0.53) |
| High | 0.27 | 0.59 | 0.34%*<br>(1.85) | 0.31%**<br>(2.24) | 0.18%<br>(0.86) | 0.17%<br>(0.80) | 0.16%<br>(1.02) |

We report monthly alphas from running regressions of excess returns of our two low-high spread portfolios against the market (Panel A), and against the Fama-French four factors (Panel B). See text for fuller description. Newey-West (1987) t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

**Table 4**
**Estimated Slope Coefficients of Beta Portfolios on HML and MOM factors**
**1968-2012**

**Panel A**

| **B/P Spread Quintiles (B/P for low beta stocks– B/P for high beta stocks)** | | | **Average beta on HML** | | | | |
|---|---|---|---|---|---|---|---|
| **Quintile** | **From** | **to** | t+12 | t+24 | t+36 | t+48 | t+60 |
| Low | -0.55 | -0.01 | 0.11 | 0.16 | 0.24 | 0.33 | 0.31 |
| 2 | -0.01 | 0.12 | 0.33 | 0.50 | 0.57 | 0.52 | 0.52 |
| 3 | 0.12 | 0.22 | 0.73 | 0.78 | 0.73 | 0.79 | 0.79 |
| 4 | 0.22 | 0.27 | 0.65 | 0.66 | 0.68 | 0.66 | 0.71 |
| High | 0.27 | 0.59 | 0.53 | 0.65 | 0.68 | 0.69 | 0.65 |

**Panel B**

| **B/P Spread Quintiles (B/P for low beta stocks– B/P for high beta stocks)** | | | **Average beta on MOM** | | | | |
|---|---|---|---|---|---|---|---|
| **Quintile** | **From** | **to** | t+12 | t+24 | t+36 | t+48 | t+60 |
| Low | -0.55 | -0.01 | 0.18 | 0.08 | 0.10 | 0.08 | 0.03 |
| 2 | -0.01 | 0.12 | 0.08 | 0.05 | 0.05 | 0.08 | 0.14 |
| 3 | 0.12 | 0.22 | 0.15 | 0.10 | 0.14 | 0.18 | 0.17 |
| 4 | 0.22 | 0.27 | 0.23 | 0.26 | 0.17 | 0.12 | 0.12 |
| High | 0.27 | 0.59 | 0.24 | 0.35 | 0.32 | 0.23 | 0.19 |

We report estimated betas on HML and MOM from running regressions of low-high spread returns on the Fama-French four factors. See text for fuller description. ). The sample period is 1968-2012 using overlapping periods.

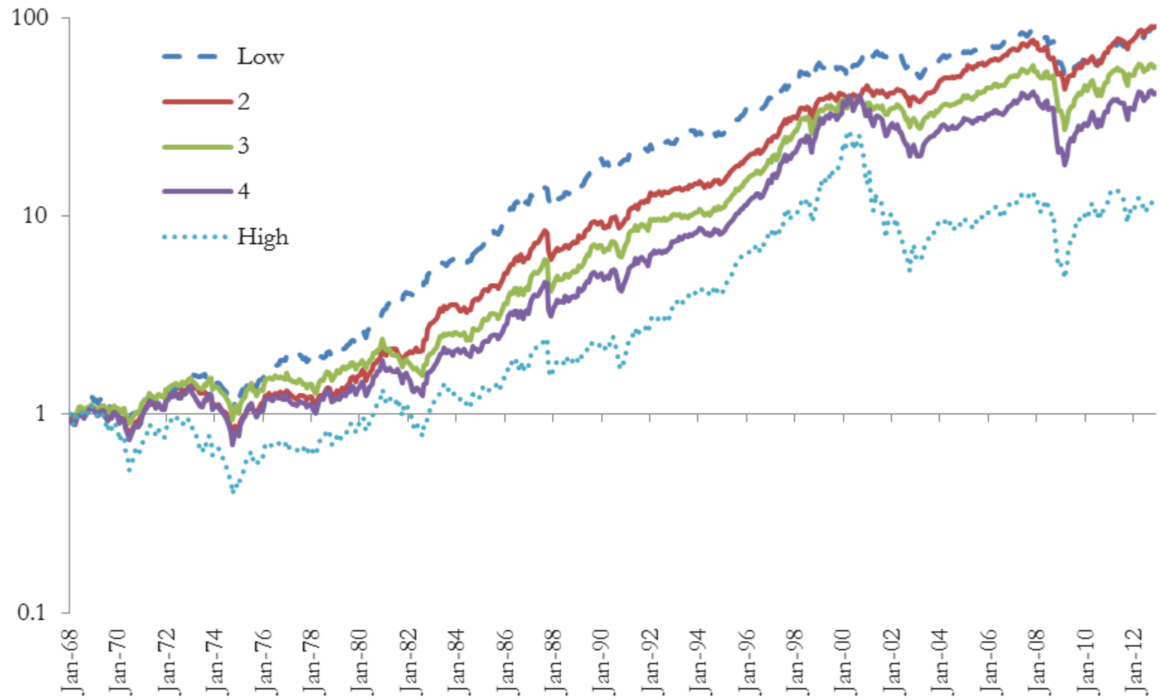
**Table 5**

**Returns on Beta spread portfolio by B/P spread (1930-2012)**

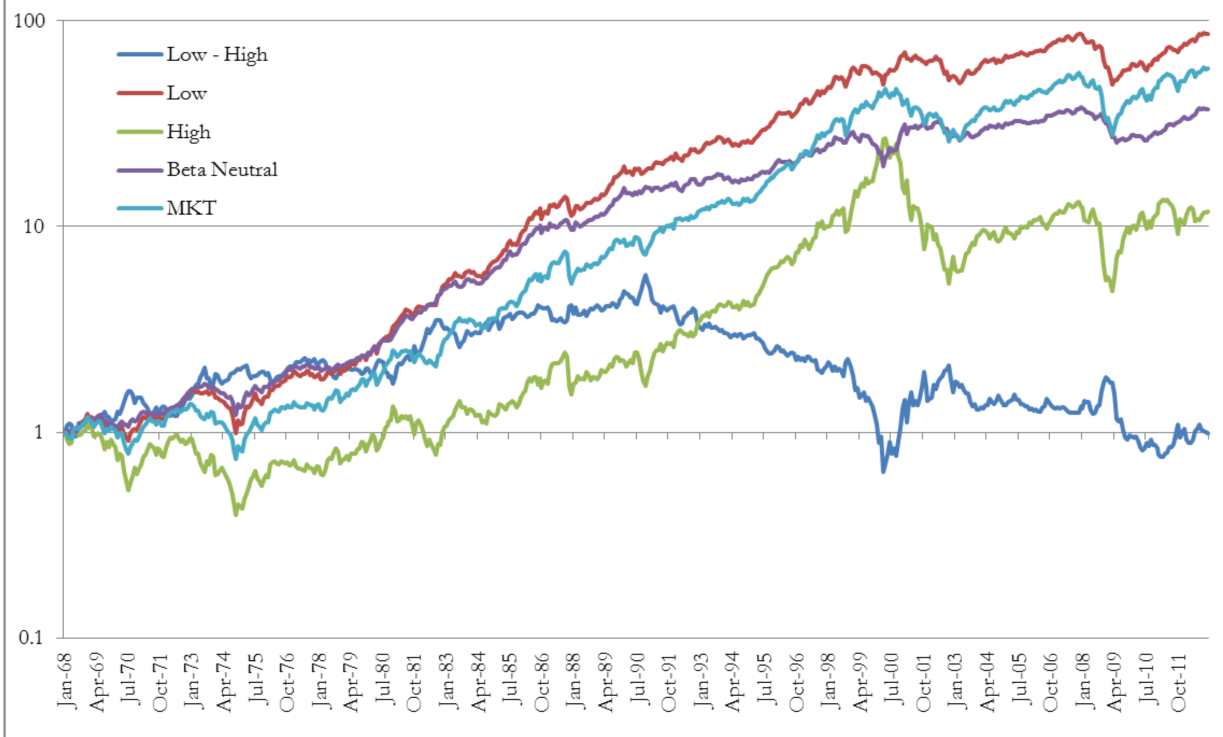
| **B/P Spread Quintiles** | | | **Future Cumulative Return on Low Beta-High Beta Strategy by B/P spread Quintile (Periods Beyond t+12 Annualized)** | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Quintile** | **From** | **to** | t+1 | t+12 | t+24 | t+36 | t+48 | t+60 |
| Low | -2.79 | -0.65 | -0.97% | -10.68% | -10.17% | -10.20% | -9.55% | -8.89% |
| 2 | -0.65 | 0.00 | -0.38% | -4.57% | -5.67% | -5.80% | -6.15% | -6.34% |
| 3 | 0.00 | 0.17 | -0.24% | 0.22% | -1.50% | 0.02% | 0.42% | 0.29% |
| 4 | 0.17 | 0.26 | 0.18% | 0.51% | 0.28% | -1.02% | -1.58% | -0.79% |
| High | 0.26 | 0.72 | 0.62% | 7.44% | 2.84% | 1.57% | 1.83% | 1.28% |

We report monthly alphas from running regressions of excess returns of our two low-high spread portfolios against the market (Panel A), and against the Fama-French four factors (Panel B). See text for fuller description. Newey-West (1987) t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

**Figure 1. Returns on Beta Quintile, January 1968-December 2012, Large-Cap Stocks**



# Figure 2. Returns on Low and High Beta Quintiles vs Market



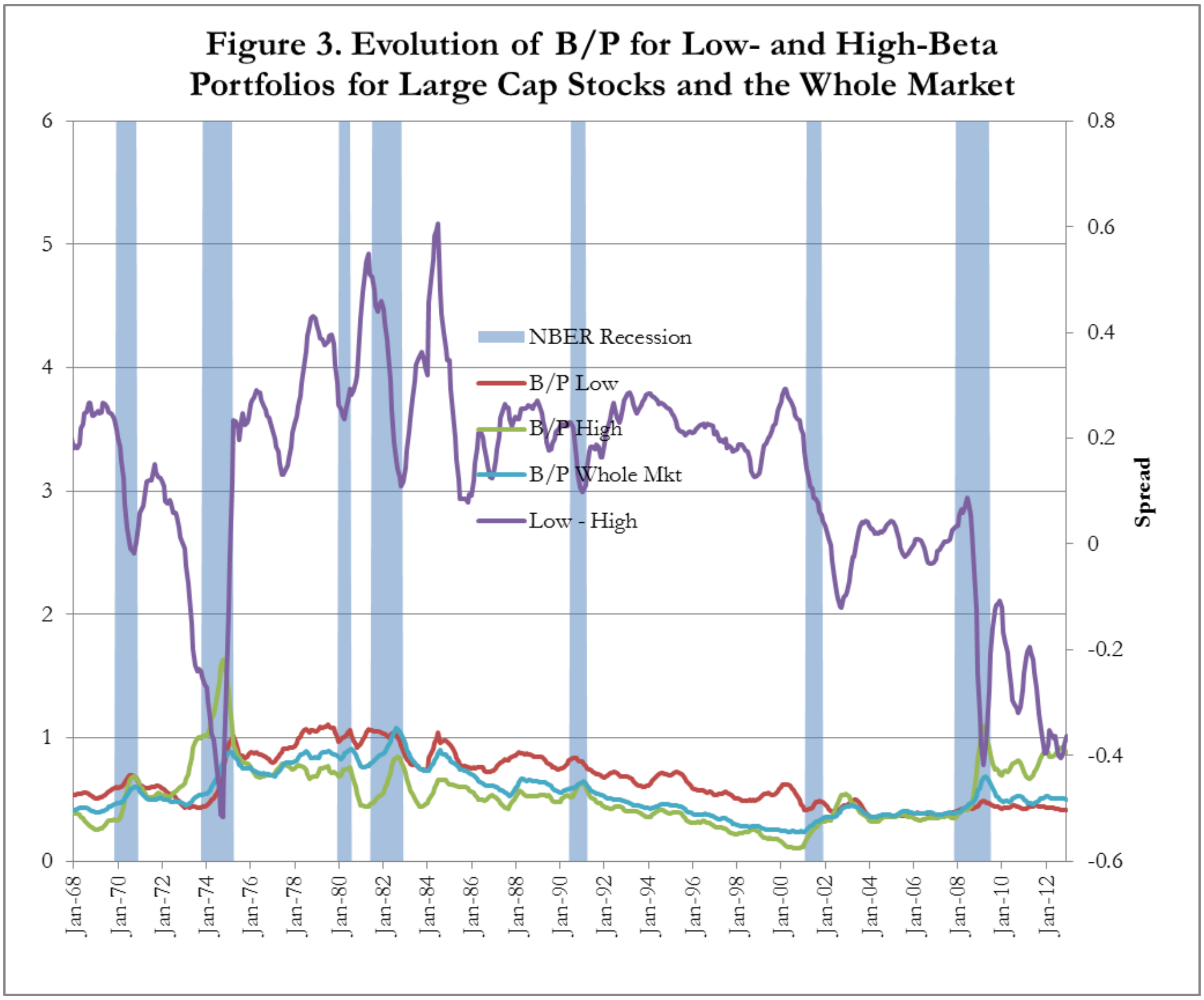
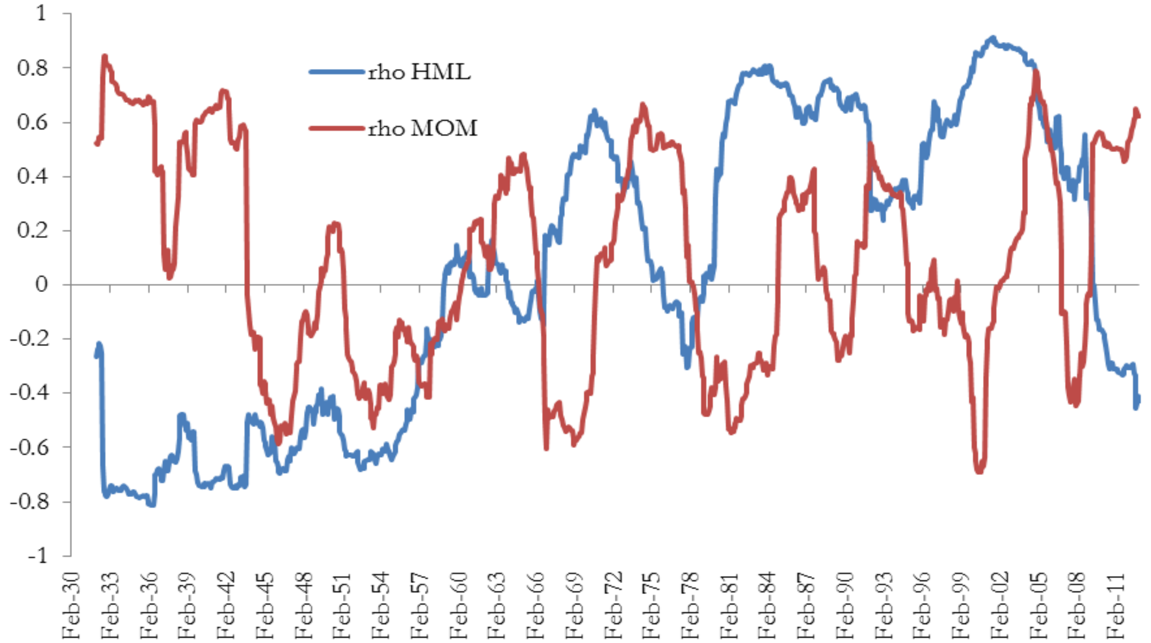


Figure 3. Evolution of B/P for Low- and High-Beta Portfolios for Large Cap Stocks and the Whole Market
NBER Recession
B/P Low
B/P High
B/P Whole Mkt
Low - High
Spread
0
1
2
3
4
5
6
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
Jan-68
Jan-70
Jan-72
Jan-74
Jan-76
Jan-78
Jan-80
Jan-82
Jan-84
Jan-86
Jan-88
Jan-90
Jan-92
Jan-94
Jan-96
Jan-98
Jan-00
Jan-02
Jan-04
Jan-06
Jan-08
Jan-10
Jan-12

**Figure 4. Rollng four-year correlation between the Low-High Risk Spread Portfolio and HML and MOM for Large Cap Stocks**



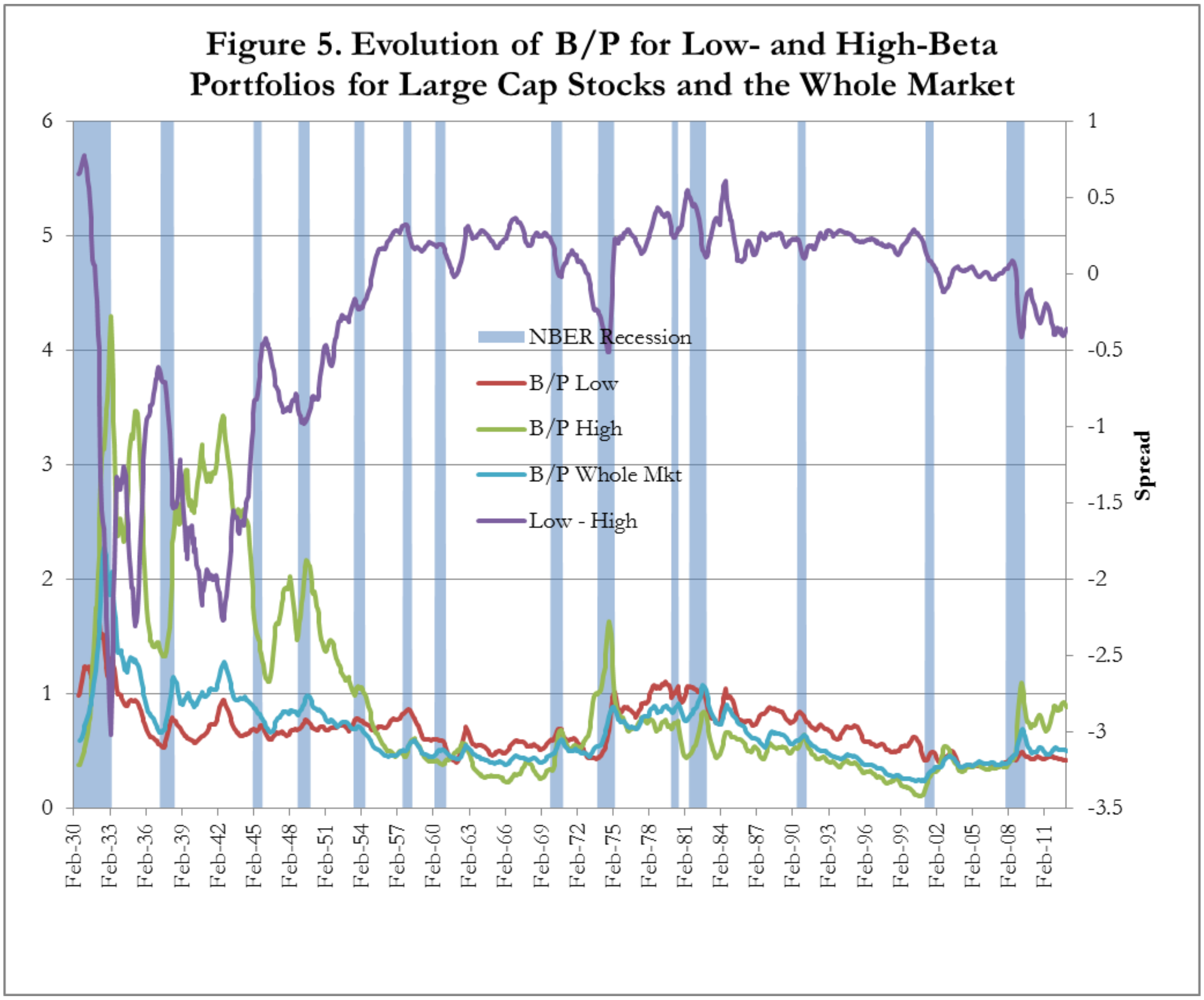


Figure 5. Evolution of B/P for Low- and High-Beta Portfolios for Large Cap Stocks and the Whole Market
NBER Recession
B/P Low
B/P High
B/P Whole Mkt
Low - High
Spread
0
1
2
3
4
5
6
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
Feb-30
Feb-33
Feb-36
Feb-39
Feb-42
Feb-45
Feb-48
Feb-51
Feb-54
Feb-57
Feb-60
Feb-63
Feb-66
Feb-69
Feb-72
Feb-75
Feb-78
Feb-81
Feb-84
Feb-87
Feb-90
Feb-93
Feb-96
Feb-99
Feb-02
Feb-05
Feb-08
Feb-11