The Low Beta Anomaly: A Decomposition into Micro and Macro Effects

Malcolm Baker[*]
Brendan Bradley
Ryan Taliaferro

September 13, 2013

Abstract

Low beta stocks have offered a combination of low risk and high returns. We decompose the anomaly into micro and macro components. The micro component comes from the selection of low beta stocks. The macro component comes from the selection of low beta countries or industries. The two parts both contribute to the low beta anomaly, with important implications for the construction of managed volatility portfolios.

[*] Malcolm Baker is professor of finance at Harvard Business School, research associate at the National Bureau of Economic Research, and senior consultant at Acadian Asset Management, Boston. Brendan Bradley is director of portfolio management at Acadian Asset Management, Boston. Ryan Taliaferro is portfolio manager at Acadian Asset Management, Boston.

Note: The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research or Acadian Asset Management.

In an efficient market, investors earn a higher return only to the extent that they bear higher risk. Despite the intuitive appeal of a positive risk-return relationship, this pattern has been surprisingly hard to find in the data, dating at least to Black (1972). For example, sorting stocks using measures of market beta or volatility shows just the opposite. Panel A of Figure 1 shows that, from 1968 through 2012 in the U.S. equity market, portfolios of low risk stocks deliver on the promise of lower risk as planned, but with surprisingly higher average returns. A dollar invested in the lowest risk portfolio grew to $81.66 while a dollar invested in the highest risk portfolio grew to only $9.76. A similar inverse relationship between risk and return appears from 1989 through 2012 in a sample of up to 31 developed equity markets shown in Panel B of Figure 1. A dollar invested in the lowest risk portfolio of global equities grew to $7.23. Meanwhile a dollar invested in the highest risk portfolio of global equities grew to only $1.20 at the end of the period. This so-called low risk anomaly suggests a very basic form of market inefficiency.

Shiller (2001) credits Paul Samuelson with the idea of separating market efficiency into two types. Micro efficiency concerns the relative pricing of individual stocks, while macro efficiency refers to the pricing of the market as a whole. Broadly speaking, inefficiencies can be examined at different levels of aggregation: at the individual stock level, at the industry level, at the country level, or, in some cases, for global equity markets.

Samuelson (1998) conjectured that capital markets have "come a long way, baby, in two hundred years toward micro efficiency of markets: Black-Scholes option pricing, indexing of portfolio diversification, and so forth. But there is no persuasive evidence, either from economic history or avant garde theorizing, that macro market inefficiency is trending toward extinction." At the heart of the difference is the fact that individual securities often have close substitutes. As Scholes (1972) shows, the availability of close substitutes facilitates low risk micro arbitrage and pins down relative prices, if there are no practical limits on arbitrage. Industry and country portfolios have fewer close substitutes, and the equity market as a whole has none. So, individual stocks, in this view, are priced more efficiently relative to each other than they are in absolute terms. Of course, limits to arbitrage are real and substitutes are never perfect, so even Samuelson's hypothesis is one of relative not absolute efficiency.

In the context of the low risk anomaly, Baker, Bradley, and Wurgler (2011) emphasize the important constraint that long only, fixed-benchmark mandates impose *on micro arbitrage*. Many institutional investors are judged not by total return relative to total risk, but instead on active return relative to active risk, or benchmark tracking error. Such benchmark oriented mandates discourage investment in low risk stocks. Despite their low risk, these stocks only become attractive relative to the tracking error they create when their anticipated return exceeds the benchmark in absolute terms. There are also limits *on macro arbitrage*. Market aggregates do not have close substitutes, and so macro arbitrage – in the usual sense of simultaneously buying low and selling fundamentally similar securities high – is largely infeasible. Standard institutional mandates and risk management practices also play a role here, typically limiting the size of benchmark relative country or industry exposures or eliminating them entirely through narrow mandates that identify a single country index as the benchmark return. French and Poterba (1991) and more recently Ahearne, Griever, and Warnock (2004) document a home bias, for example, showing that individuals often do not invest across borders.

One way of examining the relative efficiency of markets at different levels of aggregation is to aggregate or disaggregate a known anomaly into its micro and macro components. An important limitation of this approach is that anomalies change their meaning at different levels of aggregation. Ratios of fundamental to market value capture misvaluation at the individual stock level, as in Basu (1977). But, Lewellen (1999) finds little contribution from the industry level, where differences in valuation ratios might reflect varying approaches to caplitalizing investment or reporting earnings. Meanwhile, Fama and French (1998) find that predictive power reappears at even higher levels of aggregation in cross-country regressions. Likewise, Kothari and Shanken (1997) find that time series comparisons of valuation ratios for equity markets as a whole are also useful. Unlike value, beta retains the same meaning at the stock level and in country and industry portfolios, though it loses some of its variability. Its usefulness runs out for the market as a whole, where it is 1.0 by definition. Another limitation of aggregation is that econometric tests typically lose power to identify inefficiency. So, it is important to consider economic and statistical significance.

In the spirit of Samuelson, we decompose the low risk anomaly into its micro and macro components. The pattern of low risk and high return can in principle come either from the macro selection of lower risk countries and industries or from the micro selection of low risk stocks within those countries and industries. We separate the two effects by forming long-short portfolios of stocks that first hold constant ex ante country or industry level risk and examine stock selection. Then, we hold constant ex ante stock level risk and examine country or industry selection. What we find in a sample of 29 US industries and up to 31 developed countries is that micro and macro selection both contribute to the low risk anomaly, albeit for two surprisingly different reasons.

The micro selection of stocks leads to a significant reduction in risk, with only a modest difference in return. Even holding constant country or industry level risk, there is ample opportunity to form lower risk portfolios through stock selection, and these lower risk portfolios do not suffer lower returns. High risk stocks can be distinctly identified within the utility industry or in Japan, for example, but they have similar raw returns on average when compared to low risk stocks in the same industry or country grouping. This evidence supports the notion of limits to micro arbitrage in low risk stocks that come from traditional fixed-benchmark mandates. Meanwhile, the macro selection of countries in particular leads to increases in return, with only modest differences in risk. Countries that we identify as high risk ex ante are only modestly higher risk going forward, but they have distinctly lower returns. This evidence supports the limits to macro arbitrage across countries and industries.

Other researchers have examined the question of micro versus macro efficiency. Jung and Shiller (2005) show that dividend yields predict the growth in dividends at the firm level, but not at higher levels of aggregation. A higher dividend yield should intuitively be associated with lower growth in dividends, and indeed across firms this is true, suggesting a degree of micro efficiency. Somewhat pathologically, higher aggregate dividend yields predict higher, not lower, dividend growth, suggesting macro inefficiency. This parallels the more in-depth studies by Campbell (1991) and Vuolteenaho (2002) of variance decompositions of stock returns using valuation ratios. Lamont and Stein (2006) extend this logic to corporate finance. Corporate financing activities like new issuance and stock-financed mergers, which are in part designed to take advantage of market inefficiency, display greater sensitivity to aggregate movements in value than they do to individual stock price changes.

Decomposing the low risk anomaly is a particularly appealing new avenue, because beta retains its meaning in country and industry aggregations. Unlike beta, value or momentum, for example have no ex ante, risk-based theory of return predictability. So, if value, to take an example, has greater predictive power within industries than across industries, little is revealed about micro versus macro efficiency. It may simply be differences in accounting conventions, for example, across industries, which make relative value comparisons with financial statement data easier within industries.

Our results on the decomposition of the low risk anomaly into micro and macro effects have investment implications for plan sponsors and individuals alike. For individuals, it suggests that trying to exploit the mispricing through industry and sector funds or ETFs will only get you so far. While such a strategy can gain exposure to the macro effects, it cannot exploit considerable risk reduction available in micro stock selection. For institutional investors and plan sponsors, it suggests that perfunctory approaches to risk modeling and overly constrained mandates will not fully appreciate the benefits of the macro effects. Broad mandates with loose constraints and thoughtful techniques to modeling risk will do the most to exploit the low risk anomaly.

The Low Risk Anomaly

A preliminary step is confirming that the low risk anomaly is present in two sources of stock return data that are convenient for our decomposition. We sort stocks into quintiles according to ex ante market beta and form five capitalization-weighted, buy-and-hold portfolios. Theory predicts a positive relationship between risk and return. Under the Sharpe-Lintner Capital Asset Pricing Model, the relationship is linear and the slope between contemporaneously measured market beta and returns is equal to the overall market risk premium. Fortunately, the low risk anomaly does not hinge on elaborate estimations, because the empirical slope has the wrong sign.

For our analysis of industries within the U.S., we use data from the Center for Research in Securities Prices (CRSP). From CRSP we collect the monthly returns of all U.S. shares for the period January 1963 through December 2012. We also collect the corresponding data on market capitalizations to form capitalization-weighted portfolios. Each month and for each stock, we estimate a market beta using the previous 60 months of excess returns. Stocks that have fewer than 60 prior monthly returns are included if they have a history of at least 12 months.

For our analysis of countries across the developed world, we use data from Standard & Poor's Broad Market Index (BMI). From BMI we collect monthly and weekly returns and market capitalizations for common stocks for the period July 1989 through December 2012. The raw dataset contains a very small number of suspicious returns, less than –100% and greater than 1,000%, and we exclude these observations from our analysis. Market betas are estimated using the excess return of the capitalization-weighted aggregate of all stocks in the sample as the market portfolio. Returns are measured in U.S. dollars, and the risk-free rate is the U.S. Treasury bill rate from Ken French's website. Each month and for each stock, we estimate a market beta using the previous 60 weeks of returns. Stocks that have fewer than 60 prior weekly returns are included if they have a history of at least 12 weeks. We opt for a more dynamic estimation of betas in the BMI. The overall sample is shorter and a five-year period to estimate initial betas is more costly. Neither monthly nor weekly country betas perform particularly well in predicting future country portfolio betas, but weekly measures are a marginal improvement.

Figure 1 depicts the low risk anomaly graphically. In the CRSP data in Panel A, a $1 investment in the low risk quintile portfolio in 1968 compounds to $81.66 by the end of 2012. A $1 investment in the high risk quintile compounds to only $9.76. Over the shorter history of the

BMI data, a $1 investment in 1989 compounded to $7.23 in the low risk quintile and $1.20 in the high risk quintile.

To understand the statistical significance of these results, we perform a simple test in Table 1. We regress the returns of each of the resulting five portfolios, measured in excess of U.S. Treasury bill returns, on the aggregate market excess return, to find the portfolio's full-period ex post market beta and CAPM alpha. The first and third columns in Table 1 report the betas and alphas, respectively, of five CRSP portfolios. The second and fourth columns in Table 1 report the same calculations for the BMI data. For example, the portfolio formed from the CRSP stocks with the lowest betas realized a beta of 0.59 over the full period, 1968-2012. The portfolio formed from the CRSP stocks with the highest betas realized a beta of 1.61. The difference between these betas of 1.02 is both large and significant, with a *t*-statistic of 23.99. These results suggest that betas estimated from past returns are strong predictors of future betas.

More importantly, the third column in Table 1 reports the alphas for five CRSP, beta-sorted portfolios. The difference in risk-adjusted performance is stark. The least risky portfolio formed from the lowest beta stocks has an alpha of 2.27% and a *t*-statistic 2.16, while the riskiest portfolio formed from the highest beta stocks has a CAPM alpha of –4.49% and *t*-statistic of –2.70. The difference between these alphas is economically large at 6.76% and statistically significant with a *t*-statistic of 2.84. It is this last result that summarizes the low-risk anomaly: low risk stocks outperform high risk stocks on a risk-adjusted basis.

Despite a shorter history, the low risk anomaly appears to be stronger in the BMI data. The fourth column in Table 1 reports the alphas for five BMI, beta-sorted portfolios. The difference between the alphas is larger at 9.24%, with a *t*-statistic of 2.71. This is not quite an independent test of the low risk anomaly, because the samples overlap in time and in securities with the U.S. included in both. However, when we exclude the two largest countries, the U.S. and Japan, we obtain similar results both here and in the decomposition below. Our aim is to use data, with the highest quality and deepest history, for separate industry and country decompositions. We sacrifice cross country variation to double the history of our industry decomposition, and we sacrifice history to have a stable cross-country decomposition.

These preliminary results align with the literature, which dates to Black (1972), Black, Jensen, and Scholes (1972), Haugen and Heins (1975). More recently, Fama and French (1992), Falkenstein (1994) and others have observed a flat or even negative empirical relationship between risk and return. Ang, Hodrick, Xing, and Zhang (2006, 2009) focused more on volatility sorts, pointing out the poor performance of the highest volatility quantiles. Bali, Cakici, and Whitelaw (2011) develop a related measure of lottery-like risk. Hong and Sraer (2012) incorporate speculative motives to trade into an asset pricing model to explain the low risk anomaly while Frazzini and Pederson (2010) focus on the implications of leverage and margining and extend this to other asset classes. There is roughly a risk return tradeoff across long histories of asset class returns, where stocks outperform bonds, for example. But, within asset classes, the lowest risk portfolios have higher Sharpe ratios. Baker and Haugen (2012) and Blitz, Pang and van Vliet (2012) document the outperformance of low risk stocks in various markets throughout the developed and emerging world. None of these authors focus on the decomposition of the anomaly into micro and macro effects. In a current working paper, Asness, Frazzini, and Pedersen (2013) apply a different methodology to examine the contributions to the low risk anomaly of the industry and stock selection pieces. Their results are consistent with our own decomposition at the industry level.

Explanations have emphasized a combination of behavioral demand and the limits to arbitrage, including limited borrowing capacity and the delegation of stock selection, to explain the low risk anomaly. Baker, Bradley, and Wurgler (2011) survey three behavioral explanations: lottery preferences, representativeness, and overconfidence. We omit a detailed review of these here to save space. In terms of constraints, Black (1972) and Frazzini and Pedersen (2010) emphasize leverage. Karceski (2002) and Baker, Bradley, and Wurgler (2011) focus on the effects of intermediation. While Karceski describes the interaction between high beta strategies and the capture of mutual fund flows, Baker, Bradley, and Wurgler derive the implications of fixed benchmark strategies for low risk stocks using the framework in Brennan (1993). It is worth noting that these stories suggest both the overvaluation of high risk stocks and the undervaluation of low risk stocks. Our focus here is not to disentangle the absolute mispricing, but rather to examine the relative mispricing in Table 1. Assuming the behavioral demand applies to both individual stocks and market aggregates, a decomposition of the low risk anomaly can in principle help to understand the extent of the limits to micro and macro arbitrage, and the role of fixed benchmarks.

Variations on the Low Risk Anomaly

There are several important footnotes to this analysis so far. The first involves the rate of turnover and liquidity in the low risk portfolios. The second involves the benchmark model used for computing risk-adjusted returns, or alphas. The third is the measure of risk itself, which has varied in the literature.

Beta turnover and liquidity. Some measures of risk require high frequency rebalancing. For example, Ang, Hodrick, Xing, and Zhang (2006, 2009) and Bali, Cakici, and Whitelaw (2011) measure idiosyncratic risk over relatively short horizons. The results in Table 1 do not require much turnover, by contrast. For the CRSP sample, this is intuitive. The betas are computed using 60 months of data, so changes in beta estimates from month to month are small. The probability of staying in the first or fifth quintiles from one month to the next is greater than 95%, and the probability of moving out of the top or bottom two quintiles from the first or the fifth is less than 0.5%. Moreover, lagged betas show a similar ability to predict monthly returns, so turnover is of limited value. Table 2 repeats the analysis in the third column of Table 1 using betas lagged up to 12 months. Economic and statistical significance remains almost unchanged. In terms of liquidity, Baker, Bradley, and Wurgler (2011) show that Figure 1 appears more robust when attention is restricted to the largest 1,000 stocks in CRSP. While we have not modeled transaction costs as in Li, Sullivan, and Garcia-Feijoo (2013), the combination of these two facts, low turnover and the existence of the anomaly in large capitalization stocks, suggests this particular low beta strategy was an implementable one over this time period.

Benchmark models. There are several possibilities in the literature for benchmarking returns. We chose to focus on CAPM regressions for two reasons. The first is that we can parsimoniously show the impact on both risk and alpha in double sorts. With three or four measures of risk, this becomes complicated. Below, we show how firm, industry, and country level information affects portfolio risk reduction and risk-adjusted returns, which works nicely with CAPM betas. The second and related reason is that beta is a theoretically motivated measure of risk. Low beta stocks and portfolios of low beta stocks are less risky in the sense that their marginal contribution to the overall volatility of most diversified portfolios is negative.

Size, value, and momentum are other anomalies that were discovered because of their return properties not because of any clear risk-based theory.

Even if size and value can also be considered anomalous, it is still useful to ask whether beta sorts represent a different anomaly from value and size. As it turns out, low risk alphas are still statistically significant with controls for value and size. The alpha in Table 1 retains its statistical significance, but the point estimate drops from 6.76 to 4.08. What this says is that there is incremental information in beta that is not fully contained in value, and also that some of the alpha in low risk strategies can be captured through value. This is not too surprising, in that any explanation where low risk stocks are undervalued predicts that crude value measures absorb some of the low risk anomaly. Like value, momentum helps to explain some of the performance of low beta strategies. Momentum alone does not eliminate the low beta outperformance, but it also reduces its economic and statistical power somewhat. However, there is even less reason to include momentum in the benchmark. While the correlation between value or size and beta is stable, the connection between momentum and beta is not. With large market moves, momentum portfolios inherit beta risks of one type or the other, high or low. Occasionally the extreme quintiles overlap, and occasionally they contain a disjoint set of stocks. So, the low volatility anomaly has no routine, theoretical, and positive exposure to momentum as a risk factor. Rather, it is momentum that occasionally has low or high market risk. Daniel and Moskowitz (2013) show that momentum crashes have occurred disproportionately following major market declines, when past losers are high beta and past winners are low beta. These are periods when low beta stocks have also underperformed high beta stocks. This strikes us as an interesting feature of momentum, but not a reason to change the benchmark.

Measures of risk. Beta is only one measure of risk that is associated with a broader low risk anomaly. The reason we focus on beta is that any portfolio beta, including industry or country portfolios, is a simple weighted average combination of the individual security betas contained in that portfolio, at their portfolio weights. The same cannot be said of the portfolio idiosyncratic volatility. The full covariance matrix of the individual securities is needed to get from security level risk to portfolio level risk. Nonetheless, a decomposition of idiosyncratic risk, given its ability to predict stock level returns is an interesting robustness check. The main choices in measuring volatility are choosing the benchmark and choosing the time horizon. We focus on a low frequency measure of idiosyncratic volatility that draws from the same CAPM regressions described above to estimate beta. Although we do not match the approach in Ang, Hodrick, Xing, and Zhang (2006, 2009), the resulting portfolios are more stable, with lower transaction costs in implementation, and the interpretation is simpler, because the estimation window and the regression specification are identical.

A Decomposition of Micro and Macro Effects in 29 Industries

We begin with a decomposition of the low risk anomaly into separate industry and stock level effects. It is worth keeping in mind the statistical significance of the basic anomaly. There are economically large differences in both risk and risk-adjusted returns, but the statistical significance of the return differences is more modest, suggesting that we will have somewhat less power to decompose these effects definitively, and we will focus on economic effects more than statistical significance.

We group firms into industries using their primary SIC memberships, as identified by CRSP. Because four-digit SIC codes divide the sample into groups that are sometimes too small to obtain robust estimates of risk and return, we use Ken French's somewhat broader industry groupings that build on Fama and French (1997). Our industry definitions are to a degree subjective. For example, on Ken French's website, there are definitions that group stocks into 5, 10, 12, 17, 30, 38, 48, and 49 industries. In the analysis following, we use the definitions for the 30 industries, dropping the "Other" category to net 29, and we have checked that the results are not materially different using the 12-industry definitions.

Two considerations motivate our use of 30 industries. First, the 12 industry definitions leave a substantial subset of stocks categorized as "Other", while the 30 industry definitions assign a much smaller subset to this classification. Second, our methodology groups stocks into quintiles based on industry betas, and it seemed unnecessarily coarse to use 12 industry definitions to assign stocks to five quintiles. On the other hand, when there are more industries, there are fewer stocks per industry and the potential problems of using four-digit SIC codes emerge, so we did not push beyond 30 industries into finer industry definitions. Using fewer industry groupings does not necessarily tilt us in favor of finding a more robust micro effect. What matters is the link between estimated and realized industry betas, and the robustness of this relationship initially increases with the number of industries but eventually decreases as the estimation error associated with thin cells becomes relevant.

The low risk anomaly across industries. Table 3 is a prelude to the decomposition of the low risk anomaly, repeating the analysis in the first and third columns of Table 1 with industry betas in place of stock betas. A stock's industry beta is the beta of the capitalization-weighted average of the betas of the stocks within the industry: on each estimation date, the industry beta is the same for each stock in a given industry. Each month, we use quintile breakpoints to assign an approximately equal number of stocks to each of five portfolios using industry betas. All stocks in a given industry are assigned to a single quintile portfolio. We again capitalization-weight the stocks in each portfolio to find portfolio returns, and we estimate market betas and CAPM alphas. The first column suggests that historic, ex ante industry beta is able to predict ex post realized stock betas, but not as well as historic stock betas. In this column, the difference between the ex post betas of the high and low portfolios is –0.60, with a *t*-statistic of –16.69, roughly two-thirds of the spread achieved using stock betas in Table 1. Similarly, compared to the difference in ex post alphas using stocks' own betas, the second column reports a smaller and marginally significant difference in ex post alphas of 3.65%, with a *t*-statistic of 1.80. In short, using only information about industry betas and no stock level information delivers a reasonable fraction of the risk reduction and risk-adjusted return improvement of stock level sorts.

Decomposing the low risk anomaly between stocks and industries. We now turn to the main question: To what degree do macro effects contribute to the low risk anomaly? In this case, industries represent the macro dimension of the anomaly. To understand the separate contributions of industry selection and stock selection within industries, we combine the independent quintile sorts of Table 1 and Table 3 into a double sort methodology. Each month, we use independent quintile breakpoints to assign each stock to a portfolio based on its own beta and its industry beta. We capitalization-weight the stocks in the resulting 25 portfolios.

We are interested in the contribution of stock level risk measures, once industry risk has been taken into account, and we are interested in the contribution of industry level risk measures, once stock level risk has been taken into account. We can only answer these questions to the extent that these sorts do not lead to the same exact division of the CRSP sample. Figure 2 plots the fraction of stocks in each of the resulting 25 portfolios in Panel A and the fraction of market capitalization in Panel B. If these sorts led to the same division of the CRSP sample, all of the firms and the market capitalization would lie on the diagonal. The plots show that the two effects overlap considerably, especially when measured in terms of market capitalization. This is intuitive, as large capitalization firms are likely to have measures of risk that are closer to the capitalization-weighted industry beta. The plots also show that we will have some ability to separate the two effects.

As a side note, we have also considered *dependent* sorts, in addition to the independent sorts described below. We first sort stocks into quintiles using industry beta. Within each quintile, we then sort using stock level beta. This forces an equal number of stocks into each of the 25 portfolios. Our findings are largely similar using this approach, for both industries and the country analysis described below.

For each of the 25 *independent* double-sorted portfolios, we estimate an ex post beta and CAPM alpha over the full period. Table 4 reports results. The left columns report betas, and the right columns report alphas. In the left columns, betas are widely dispersed and tend to increase from top to bottom and from left to right. For example, the first data column reports the betas of portfolios formed from stocks in low-beta industries: reading down the column, portfolio betas increase monotonically from 0.54 to 1.48 within this subsample. Similarly, the fifth data column reports betas of portfolios formed from stocks in high-beta industries, and the range of portfolio betas within this subsample also is large, increasing from 0.87 to 1.64. By contrast, rows display much less variation in portfolio betas. For example, the “Low” row, which forms portfolios from stocks with the lowest betas, shows that betas range from 0.54 to 0.87 for stocks in the lowest and highest beta industries. Among high risk stocks in the “High” row, the industry effect is even smaller. In this subsample, stocks in the highest-beta industries have an average beta of 1.64 compared to an average beta of 1.48 for stocks in the lowest-beta industries.

The statistics at the bottom of the panel summarize these patterns. The first is a *pure industry effect*, measured as the average of the differences between high beta and low beta industries, controlling for stock-level risk. This is the average of the differences reported in the “Low – High” column. The second is a *pure stock effect*, measured as the average of the differences between high beta and low beta stocks, controlling for industry risk. Again, this is the average of the differences reported in the “Low – High” row. Our ability to find low risk portfolios through the selection of low risk stocks within industries, at a –0.82 reduction in beta, is about four times as large as our ability to find low risk portfolios through the selection of low risk industries within stock risk groups. These results are consistent with stock level beta, as estimated from historical data, being a much better predictor of future beta than industry beta. However, both a stock level historical beta and its industry level historical beta, each relative to the other, have incremental predictive power for future beta.

The *t*-statistics in Table 4 are computed taking into account the empirical covariance among the 25 double-sorted portfolios. To be specific, we use a seemingly unrelated regression model that allows regression errors to be contemporaneously correlated among the 25 regressions, but that assumes zero autocorrelations or cross-autocorrelations. Measures of risk and differences in risk are highly statistically significant. Differences in return are harder to detect in the data.

The right panel of Table 4 reports alphas for the double-sorted portfolios. Alphas tend to decrease from top to bottom and from left to right. The "Low – High" column reports differences in alphas between stocks in low-beta and high-beta industries, controlling for the stocks' own betas. The first summary statistic reports the average of these differences, a pure industry effect of 1.53%. Similarly, the "Low – High" row reports the differences in alphas between low beta stocks and high beta stocks, controlling for industry beta. The second summary statistic reports the average of these differences, a pure stock effect of 4.44%. Historically, both industry selection and stock selection have made material contributions to the outperformance of low-risk investing strategies. We cannot rule out that the industry effect happened by chance, though our power to reject this null hypothesis is limited.

The beta and alpha estimates in Table 4 suggest that pure stock alpha – the micro effect – and pure industry alpha – the macro effect – arise for different reasons. The pure industry alpha of 1.53% is present in spite of a small cross-industry beta difference of –0.22. By implication, the industry alpha obtains as a consequence of cross industry portfolios exhibiting differences in returns, with modest differences in risk. In contrast, the pure stock alpha of 4.44% is present alongside a dramatic difference in within industry beta of –0.82. By implication, the stock alpha obtains as a consequence of within industry portfolios exhibiting material differences in risk, with a more limited difference in returns.

A Decomposition of Micro and Macro Effects in up to 31 Developed Country Markets

Another way to slice the data is geographically. Just as some industries such as utilities and health care are less sensitive to global equity markets, some regions and countries are also thought to have different risk properties. Japan, for example, has a low correlation with global equity markets in its recent history. Next, we turn to decomposing the low risk anomaly into country and stock effects.

Developed BMI includes Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States in the sample of developed markets. In addition, several more countries are included or excluded at some point during the sample. To avoid any lookahead bias, we follow the point-in-time S&P decisions and include these countries in the developed market sample whenever S&P labels them as such. These are the Czech Republic, Greece, Hungary, Iceland, Israel, Luxembourg, Malaysia, Portugal, Slovenia, and South Korea. Each month and for each stock we estimate a stock beta with respect to the global equity market using the previous 60 weeks of returns, measured from Wednesday to Wednesday. Stocks with a shorter history than 60 weeks are included if they have at least 12 weeks of returns. We define the global equity market as the capitalization-weighted average return of the entire BMI developed market sample. We also measure an analogous country beta. Each stock is mapped to a country, and the stock's country beta is the capitalization-weighted average of the betas of each stock within the country: on each estimation date, the country beta is the same for each stock in a given country.

The low risk anomaly across countries. In what follows, we repeat the industry analysis for countries in the BMI sample. As before, Table 5 is a prelude to the decomposition of the low risk anomaly, repeating the analysis in the second and fourth columns of Table 1 with country betas in place of stock betas. The first column suggests that historic, ex ante country beta is able to predict ex post realized stock betas, but like industries not as well as historic stock betas. In this column, the difference between the ex post betas of the high and low portfolios is –0.55, with a *t*-statistic of –8.78, roughly half of the spread achieved using stock betas in Table 1. The alpha differences are somewhat stronger than industry sorts. The second column shows a difference in ex post alphas that is smaller than Table 1, but still reasonably large at 6.86 with a *t*-statistic of 1.97. In short, using only information about country betas and no stock level information delivers roughly half the risk reduction and about two-thirds of the risk-adjusted return improvement of stock level sorts. This combination of a substantial risk-adjusted return difference and lower risk reduction is a preview of the decomposition. As we will see, unlike the industry analysis, there is something extra in the country beta sorts, in terms of total returns, that is not captured in the stock beta sorts of Table 1.

Decomposing the low risk anomaly between stocks and countries. We now ask to what degree macro effects contribute to the low risk anomaly, but, in this case, countries represent the macro dimension of the anomaly. To understand the separate contributions of country selection and stock selection within countries, we repeat the independent quintile sorts of Table 4 in Table 6. Each month, we use independent quintile breakpoints to assign each stock to a portfolio based on its own beta and its country beta. We capitalization-weight the stocks in the resulting 25 portfolios.

We are interested in the contribution of stock level risk measures, once country risk has been taken into account, and we are interested in the contribution of country level risk measures, once stock level risk has been taken into account. We can only answer these questions to the extent that these sorts do not lead to the same exact division of the BMI sample. Figure 3 plots the fraction of stocks in each of the resulting 25 portfolios in Panel A and the fraction of market capitalization in Panel B. If these sorts led to the same division of the BMI sample, all of the firms and the market capitalization would lie on the diagonal. The plots again show that the two effects overlap considerably, especially when measured in terms of market capitalization.

For each of the 25 independent double-sorted portfolios, we estimate an ex post beta and CAPM alpha over the full period. In Table 6, the left columns report betas, and the right columns report alphas. In the left columns, betas are widely dispersed and tend to increase from top to bottom and from left to right. For example, the first data column reports the betas of portfolios formed from stocks in low-beta countries: reading down the column, portfolio betas range from 0.52 to 1.62 within this subsample. Similarly, the fifth data column reports betas of portfolios formed from stocks in high-beta countries, and the range of portfolio betas within this subsample also is large, from 0.65 to 1.67. By contrast, rows display even less variation in portfolio betas than industry sorts delivered. For example, the "Low" row, which forms portfolios from stocks with the lowest betas, shows that betas range from 0.52 to 0.65 for stocks in the lowest and highest beta countries.

The statistics at the bottom of the panel summarize these patterns. The first is a *pure country effect*, measured as the average of the differences between high beta and low beta countries, controlling for stock-level risk. The second is a *pure stock effect*, measured as the average of the differences between high beta and low beta stocks, controlling for country risk. Our ability to find low risk portfolios through the selection of low risk stocks within countries, at a –1.01 reduction in beta, is 50 times as large as our ability to find low risk portfolios through the selection of low risk countries within stock risk groups. These results are consistent with stock level beta, as estimated from historical data, being a much better predictor of future beta than its country beta. This time the incremental predictive power of country level historical beta is closer to zero, in both economic and statistical terms.

The right panel of Table 1 reports alphas for the double-sorted portfolios. Alphas tend to decrease from top to bottom and from left to right. The average of these differences within each row is a pure country effect of 6.22%. The average of these differences within each column is a pure stock effect of 5.40%. Both are statistically significant at the 10% level. That is, historical data suggest the low risk anomaly is present both within and across countries.

In short, the same picture emerges with countries as we saw with industries. The beta and alpha estimates in Table 6 suggest that pure stock alpha – the micro effects – and pure country alpha – the macro effect – arise for different reasons. The pure country alpha of 6.22% is present in spite of no cross-country beta difference. By implication, the country alpha obtains as a consequence of cross country portfolios exhibiting material differences in returns, with modest differences in risk. In contrast, the pure stock alpha of 5.40% is present alongside a dramatic difference in within country beta of –1.01. By implication, the stock alpha obtains as a consequence of within country portfolios exhibiting material differences in risk, with modest differences in returns.

Idiosyncratic Risk

The same analysis can be done with idiosyncratic risk instead of beta. But, the process requires a bit more decision making. In particular, the industry contribution could be measured with the idiosyncratic risk of aggregated industry portfolios, or it could be measured with the average of firm-level idiosyncratic risk within the industry. The first measures the risk of the industry, the other measures how risky the stocks are within the industry. We opt for the second approach for both practical and theoretical reasons. Practically, our intuition is that the idiosyncratic volatility of the industry average portfolio would perhaps be lower than all of the individual stocks, because of the benefits of diversification, and it might be mechanically related to the number of firms within each industry or country. Theoretically, we view the demand arising at the stock level, so that an industry with lots of high risk stocks generates more aggregate demand than an industry with few.

This foreshadows what we find in the data. We repeat Table 4 and Table 6 using idiosyncratic risk instead of beta, and we show the summary results in Table 7. The first row of each panel is a *pure industry effect* or a *pure country effect*, measured as the average of the differences between high and low idiosyncratic risk industries and countries, controlling for stock-level idiosyncratic risk. The second row of each panel is a *pure stock effect*, measured as the average of the differences between high and low idiosyncratic risk stocks, controlling for industry or country idiosyncratic risk. What we find is that the idiosyncratic risk effect is almost entirely a micro phenomenon. 96% comes from a pure stock effect in the CRSP industry sample. 86% comes from a pure stock effect in the BMI country sample. Idiosyncratic risk is like valuation ratios, in the sense that the intuition does not necessarily aggregate. What matters is whether a stock is risky relative to a stock in its category more than the category average.

Conclusion: Samuelson's Dictum and the Implications for Managed Volatility Strategies

The decomposition of the low risk anomaly has both theoretical and practical implications. The superior performance of lower risk stocks that is evident in Figure 1 in both U.S. and international markets is a very basic form of market inefficiency. It has both micro and macro components. The micro component arises from the selection of lower risk stocks, holding country and industry risk constant. The macro component arises from the selection of lower risk industries and countries, holding stock level risk constant.

In theory, market inefficiency arises from some combination of less than fully rational demand and the limits to arbitrage. Shiller (2001) has attributed to Samuelson the hypothesis that macro inefficiencies are quantitatively larger than micro efficiencies. In contrast, we find that the contribution to the low risk anomaly is of similar magnitude across micro and macro effects. While stock selection leads to higher alpha through a combination of significant risk reduction with modest return improvements, country selection leads to higher alpha through a combination of significant return improvements and modest risk reduction. Industry selection is relatively modest and the extra alpha cannot be distinguished from zero statistically. We view this as affirmation of a modified version of Samuelson's dictum. Namely, micro efficiency holds only up to the limits of arbitrage. The constraint of fixed benchmark mandates makes low risk stocks unattractive to many institutional investors. Macro inefficiency is present for countries more so than for industries, perhaps because arbitrage is more limited across countries than across industries.

The absence of material risk reduction from the macro selection of industries and countries suggests two things. The first is that pure country or industry risk prediction is hard, compared to predicting the relative risk of individual stocks. The second is that, to the extent this anomaly arises because of investor demand for high risk aggregations of stocks, this demand is in large part backward looking. The pattern of returns suggests that behavioral demand tilts towards sectors and countries that have experienced relatively higher risk in the past.

In practice, the incremental value of industry and country selection, even holding stock level risk constant, suggests that the use of a risk model in beta estimation that includes fixed country and industry effects is preferable to simple stock level sorts on beta or volatility. This has been especially true in global portfolios, where the incremental value of estimating country level risk was significant. Moreover, because country and industry exposures have generated incremental alpha, a global mandate with somewhat relaxed country and industry constraints would have delivered higher risk-adjusted returns.

We thank Ely Spears and Adoito Haroon for excellent research assistance. Baker gratefully acknowledges the Division of Research of the Harvard Business School for financial support.

References

Ahearne, Alan, William Griever, and Francis Warnock. 2004. "Information Costs and Home Bias: An Analysis of US Holdings of Foreign Equities." *Journal of International Economics*, vol. 62, no. 2 (July):313–336.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. 2006. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance*, vol. 61, no. 1 (February):259-299.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. 2009. "High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence." *Journal of Financial Economics*, vol. 91, no. 1 (January):1-23.

Asness, Cliff, Andrea Frazzini, and Lasse H. Pedersen. 2013. "Low-Risk Investing without Industry Bets." Working paper, AQR Capital Management (May).

Baker, Malcolm, Brendan Bradley, and Jeffrey Wurgler. 2011. "Benchmarks as Limits to Arbitrage: Understanding the Low-Volatility Anomaly." *Financial Analysts Journal*, vol. 67, no. 1 (January/February):40-54.

Baker, Nardin, and Robert A. Haugen. 2012. "Low Risk Stocks Outperform within All Observable Markets of the World." SSRN Working Paper 205543 (April).

Bali, Turan, Nusret Cakici, and Robert F. Whitelaw. 2011. "Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns." *Journal of Financial Economics*, vol. 99, no. 2 (February):427-446.

Basu, S. 1977. "Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of Market Efficiency." *Journal of Finance*, vol. 32, no. 3 (June):663-682.

Black, Fischer. 1972. "Capital Market Equilibrium with Restricted Borrowing." *Journal of Business*, vol. 45, no. 3 (July):444-455.

Black, Fischer, Michael C. Jensen, and Myron Scholes. 1972. "The Capital Asset Pricing Model: Some Empirical Tests." In *Studies in the Theory of Capital Markets*. Edited by Michael C. Jensen. New York: Praeger.

Blitz, David, Juan Pang and Pim van Vliet. 2012. "The Volatility Effect in Emerging Markets." SSRN Working Paper 2050863 (April).

Brennan, Michael. 1993. "Agency and Asset Pricing." Working paper, University of California, Los Angeles (May).

Campbell, John. 1991. "A Variance Decomposition for Stock Returns." *Economic Journal*, vol. 101, no. 405 (March):157–79.

Daniel, Kent, and Moskowitz, Tobias. 2013. "Momentum Crashes." Working paper, Columbia University (April).

Falkenstein, Eric. 1994. "Mutual Funds, Idiosyncratic Variance, and Asset Returns." Dissertation, Northwestern University.

Fama, Eugene F., and Kenneth R. French. 1992. "The Cross-Section of Expected Stock Returns." *Journal of Finance,* vol. 47, no. 2 (June):427-465.

Fama, Eugene F., and Kenneth R. French. 1997. "Industry Costs of Equity." *Journal of Financial Economics*, vol. 43, no. 2 (February):153–193.

Fama, Eugene F., and Kenneth R. French. 1998. "Value versus Growth: The International Evidence." *Journal of Finance*, vol. 53, no. 6 (December):1975-1999.

Frazzini, Andrea, and Lasse H. Pedersen. 2010. "Betting Against Beta." Working paper, New York University (May).

French, Kenneth R., and James Poterba. 1991. "Investor Diversification and International Equity Markets." *American Economic Review*, vol. 81, no. 2 (May):222-226.

Haugen, Robert A., and A. James Heins. 1975. "Risk and the Rate of Return on Financial Assets: Some Old Wine in New Bottles." *Journal of Financial and Quantitative Analysis,* vol. 10, no. 5 (December):775-784.

Hong, Harrison, and David Sraer. 2012. "Speculative Betas." Working paper, Princeton University (August).

Jung, Jeeman, and Robert J. Shiller. 2005. "Samuelson's Dictum and the Stock Market." *Economic Inquiry*, vol. 43, no. 2 (April):221–228.

Karceski, Jason. 2002. Returns-Chasing Behavior, Mutual Funds, and Beta's Death." *Journal of Financial and Quantitative Analysis*, vol. 37, no. 4 (December):559–594.

Kothari, S. P., and Jay Shanken. 1997. "Book-to-Market, Dividend Yield, and Expected Market Returns: A Time-Series Analysis." *Journal of Financial Economics*, vol. 44, no. 2 (May):169-203.

Lamont, Owen, and Jeremy C. Stein. 2006. "Investor Sentiment and Corporate Finance: Micro and Macro." *American Economic Review*, vol. 96, no. 2 (May):147-151.

Lewellen, Jonathan. 1999. "The Time-Series Relations among Expected Return, Risk, and Book-to-Market." *Journal of Financial Economics*, vol. 54, no. 1 (October):5-43.

Li, Xi, Rodney Sullivan, and Luis Garcia-Feijoo. 2013. "The Limits to Arbitrage and the Low-Volatility Anomaly." *Financial Analysts Journal*, forthcoming.

Scholes, Myron. 1972. "The Market for Securities: Substitution versus Price Pressure and the Effects of Information on Share Prices." *The Journal of Business*, vol. 45, no. 2 (April):179-211.

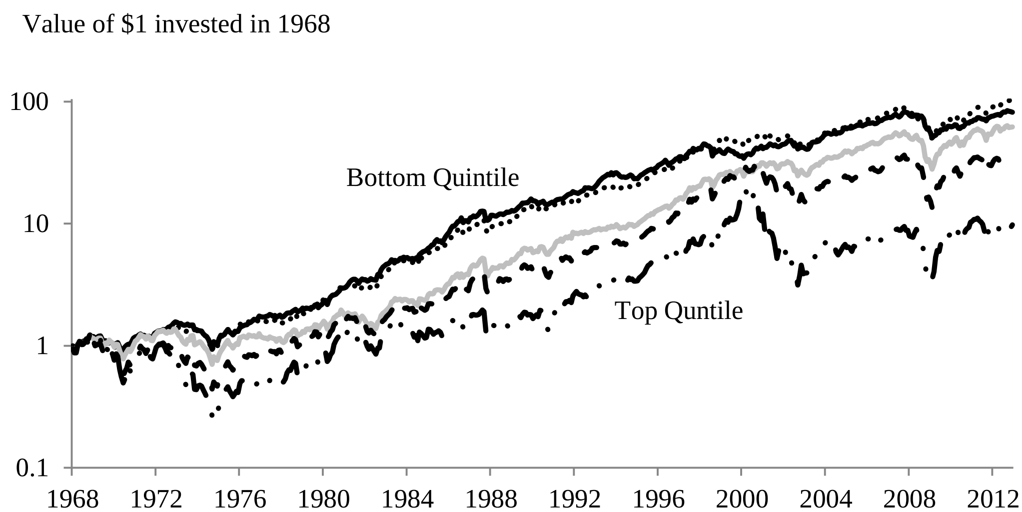
Samuelson, Paul. 1998. "Summing up on Business Cycles: Opening Address." In *Beyond Shocks: What Causes Business Cycles*. Edited by Jeffrey C. Fuhrer and Scott Schuh. Boston: Federal Reserve Bank of Boston.

Shiller, Robert J. 2001. *Irrational exuberance*. New York: Broadway Books.

Vuolteenaho, Tuomo. 2002. "What Drives Firm-Level Stock Returns?" *Journal of Finance*, vol. 57, no. 1 (February):233– 64.

Figure 1. Cumulative returns of five portfolios formed on stocks' prior betas for U.S. 1968-2012 and developed markets 1989-2012. At the beginning of each month, we use quintile breakpoints to assign each stock in the CRSP database (U.S., Panel A) and in S&P's Broad Market Index (BMI) database (developed markets, Panel B) to one of five portfolios based on its beta, estimated using the prior 60 (minimum 12) months (Panel A) or weeks (Panel B) of returns. We capitalization-weight the stocks in the resulting five portfolios, and we plot the cumulative returns of investing one U.S. dollar in each. In Panel B, countries included for the full sample are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States; countries included for part of the sample are the Czech Republic, Greece, Hungary, Iceland, Israel, Luxembourg, Malaysia, Portugal, Slovenia, and South Korea. Betas are calculated with respect to the capitalization-weighted portfolio of U.S. stocks using monthly returns (Panel A) and with respect to the capitalization-weighted portfolio of developed market stocks using weekly returns (Panel B). All returns are measured in U.S. dollars. Returns greater than 1,000% and less than –100% are excluded from the BMI database. Observation windows are January 1968 through December 2012 (Panel A) and November 1989 through December 2012 (Panel B).

Panel A. Cumulative returns for five portfolios formed on U.S. stocks' prior 60-month betas



Panel B. Cumulative returns for five portfolios formed on developed market stocks' prior 60-week betas

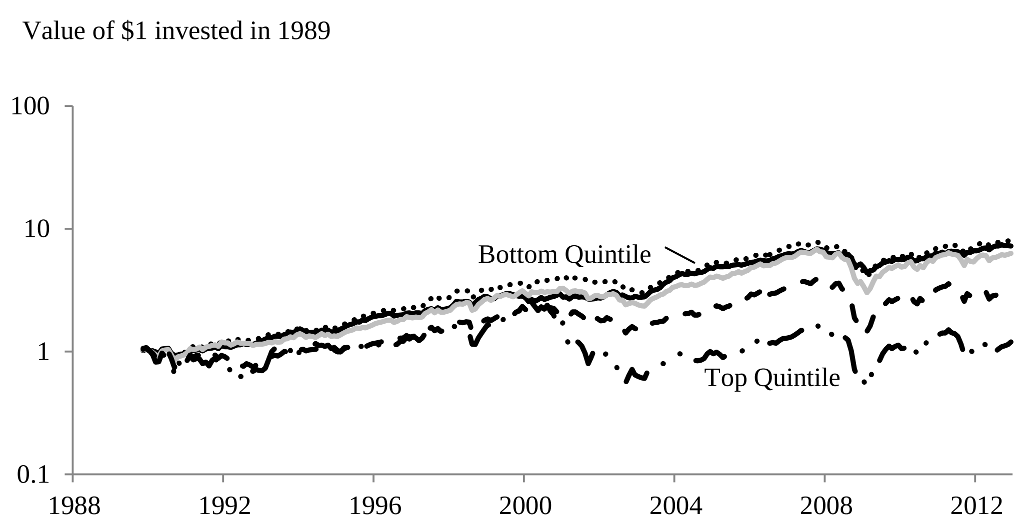
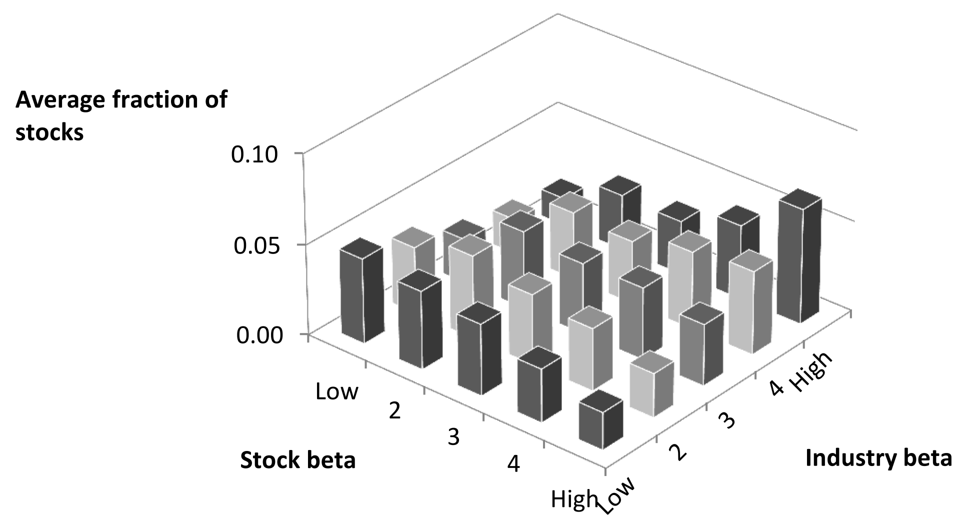


Figure 2. Distribution of stocks across portfolios formed jointly on stocks' betas and their industry betas, U.S. 1968-2012. At the beginning of each month, we use independent quintile breakpoints to assign each stock in the CRSP database to a portfolio based on its own beta and its industry's beta, where stocks' betas estimated using the prior 60 months (minimum 12 months) of returns and industry betas are the capitalization weighted average of the industry constituent stock betas. Industries are formed using Ken French's thirty industries, available on his website, with the exception of the industry "Other" which we exclude. Vertical bars denote the time-series average fraction of stocks (Panel A) or fraction of market capitalization (Panel B) in each portfolio. Observation window is January 1968 through December 2012.

Panel A. Average distribution of stocks across double-sorted portfolios



Panel B. Average distribution of market capitalization across double-sorted portfolios

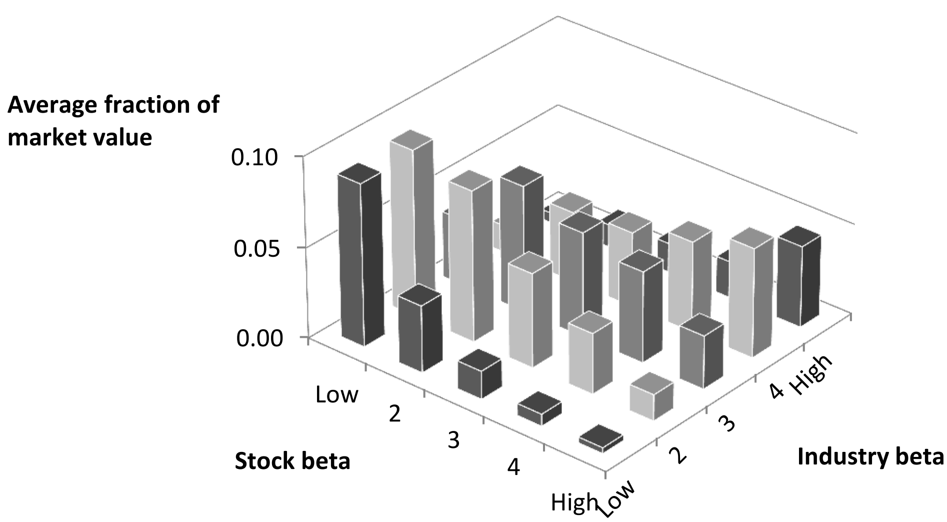
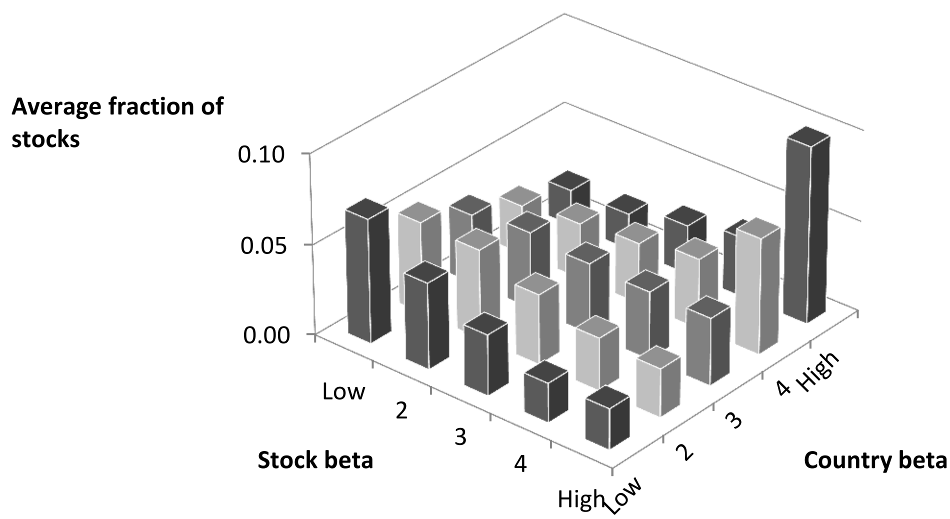


Figure 3. Distribution of stocks across portfolios formed jointly on stocks' betas and their country betas, developed markets 1989-2012. At the beginning of each month, we use independent quintile breakpoints to assign each stock in the S&P Broad Market Index (BMI) developed markets database to a portfolio based on its own beta and its country's beta, where stocks' betas are estimated using the prior 60 weeks (minimum 12 weeks) of returns and country betas are the capitalization-weighted averages of the betas of constituent stocks, and where all returns are measured in U.S. dollars. Returns greater than 1,000% and less than –100% are excluded. Vertical bars denote the time-series average fraction of stocks (Panel A) or fraction of market capitalization (Panel B) in each portfolio. Observation window is November 1989 through December 2012.

Panel A. Average distribution of stocks across double-sorted portfolios



Panel B. Average distribution of market capitalization across double-sorted portfolios

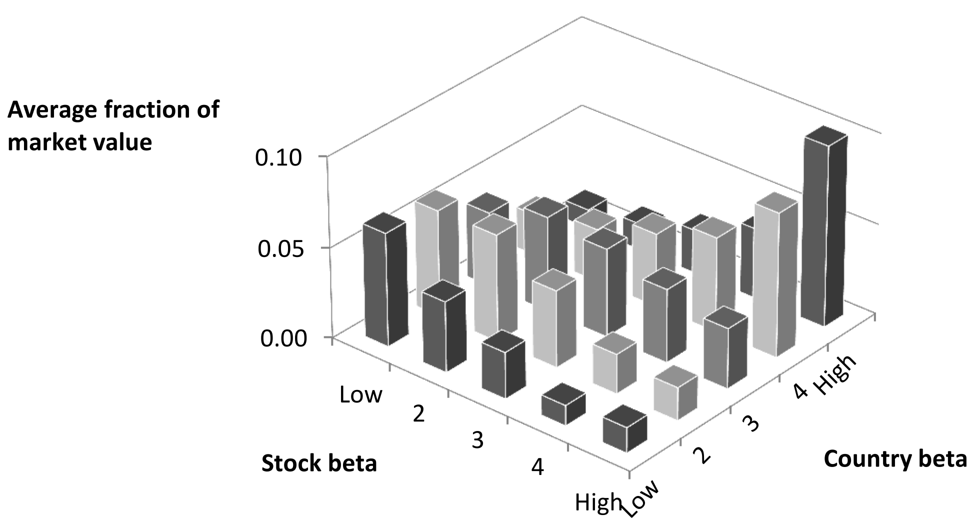


Table 1. CAPM betas and annualized alphas for portfolios formed on stocks' prior betas. We source data from CRSP from January 1968 through December 2012 and from S&P BMI from November 1989 through December 2012. At the beginning of each month, we use quintile breakpoints to assign each stock to a portfolio based on its own beta. Betas in the CRSP sample are estimated using the prior 60 months (minimum 12 months) of returns. Betas in the BMI sample are estimated using the prior 60 weeks (minimum 12 weeks) of returns, where all returns are measured in U.S dollars. For each set of breakpoints, we capitalization-weight the stocks in the resulting five portfolios, and we regress each portfolio's monthly excess returns on a constant and the market excess returns to find full-period *ex post* CAPM betas (left columns) and alphas (right columns). To compute excess returns, we use the U.S. government one-month (T-bill) rate as the risk-free rate. Panel A reports point estimates for these regressions, and Panel B reports corresponding *t*-statistics. Countries included for the full sample are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States; countries included for part of the sample are the Czech Republic, Greece, Hungary, Iceland, Israel, Luxembourg, Malaysia, Portugal, Slovenia, and South Korea. Returns greater than 1,000% and less than –100% are excluded. For CRSP, the market portfolio is from Ken French's web site. For BMI, the market portfolio is the capitalization-weighted portfolio of all included stocks.

	CAPM β		CAPM α (% p.a.)	
	Portfolios formed on:		Portfolios formed on:	
	CRSP Stock β	BMI Stock β	CRSP Stock β	BMI Stock β
Panel A. Point estimates				
Low	0.59	0.47	2.27	3.74
2	0.76	0.69	2.10	3.60
3	0.98	0.88	0.28	2.01
4	1.24	1.16	–1.52	–1.32
High	1.61	1.69	–4.49	–5.50
Low – High	–1.02	–1.22	6.76	9.24
Panel B. *t*-statistics				
Low	31.24	18.42	2.16	2.62
2	49.56	30.98	2.45	2.92
3	72.75	46.05	0.37	1.89
4	85.93	69.22	–1.89	–1.42
High	54.09	41.95	–2.70	–2.45
Low – High	–23.99	–19.89	2.84	2.71

Table 2. CAPM annualized alphas for portfolios formed on stocks' prior betas. We repeat the analysis in Table 1, using lagged values of beta. We source data from CRSP from January 1968 through December 2012. At the beginning of each month, we use quintile breakpoints to assign each stock to a portfolio based on its own beta. Betas in the CRSP sample are estimated using the prior 60 months (minimum 12 months) of returns. For each set of breakpoints, we capitalization-weight the stocks in the resulting five portfolios, and we regress each portfolio's monthly excess returns on a constant and the market excess returns to find full-period *ex post* CAPM alphas. To compute excess returns, we use the U.S. government one-month (T-bill) rate as the risk-free rate. Panel A reports point estimates for these regressions, and Panel B reports corresponding *t*-statistics.

	CAPM α (% p.a.)			
	Portfolios formed on:			
	CRSP Stock β	CRSP t-2 Stock β	CRSP t-3 Stock β	CRSP t-12 Stock β
Panel A. Point estimates				
Low	2.27	2.29	1.82	2.00
2	2.10	1.80	1.66	1.87
3	0.28	0.27	0.26	0.05
4	–1.52	-1.34	-1.06	-0.98
High	–4.49	-4.81	-4.65	-3.57
Low – High	6.76	7.10	6.48	5.58
Panel B. *t*-statistics				
Low	2.16	2.20	1.72	1.92
2	2.45	2.10	1.95	2.22
3	0.37	0.37	0.34	0.06
4	–1.89	-1.69	-1.36	-1.32
High	–2.70	-2.98	-2.86	-2.36
Low – High	2.84	3.05	2.76	2.52

Table 3. CAPM betas and annualized alphas for portfolios formed on prior 60-month industry betas, U.S. 1968-2012. At the beginning of each month, we use quintile breakpoints to assign each stock in the CRSP database of U.S. stocks to a portfolio based on its industry beta. Industry betas are estimated by forming industry portfolios from the stocks in each industry using the prior 60 months (minimum 12 months) of returns. At each moment in time, all stocks in a given industry receive the same industry beta which we calculate as the capitalization-weighted average of the betas of the constituent stocks. For each set of breakpoints, we capitalization-weight the stocks in the resulting five portfolios, and we regress each portfolio's monthly excess returns on a constant and the market excess returns to find full-period *ex post* CAPM betas (left column) and alphas (right column). Panel A reports point estimates for these regressions, and Panel B reports corresponding *t*-statistics. Industries are formed using Ken French's thirty industries, available on his website, with the exception of the industry "Other" which we exclude. Observation window is January 1968 through December 2012.

	CAPM β	CAPM α (% p.a.)
	Portfolios formed on:	Portfolios formed on:
	Industry β	Industry β
Panel A. Point estimates		
Low	0.71	2.25
2	0.92	2.50
3	0.97	–1.33
4	1.07	–0.40
High	1.31	–1.39
Low – High	–0.60	3.65
Panel B. *t*-statistics		
Low	37.29	2.11
2	52.91	2.58
3	54.38	–1.34
4	52.09	–0.35
High	58.20	–1.10
Low – High	–16.69	1.80

Table 4. CAPM betas and annualized alphas for portfolios formed jointly on prior 60-month betas and prior 60-month industry betas, U.S. 1968-2012. At the beginning of each month, we use independent quintile breakpoints to assign each stock in the CRSP database to a portfolio based on its own beta and its industry beta, where stocks' betas are estimated using the prior 60 months (minimum 12 months) of returns and industry betas are the capitalization-weighted averages of the betas of their constituent stocks. We capitalization-weight the stocks in the resulting 25 portfolios, and we regress each portfolio's monthly excess returns on a constant and the market excess returns to find full-period *ex post* CAPM betas (left columns) and alphas (right columns). Panel A reports point estimates for these regressions, and Panel B reports corresponding *t*-statistics. Industries are formed using Ken French's thirty industries, available on his website, with the exception of the industry "Other" which we exclude. Observation window is January 1968 through December 2012.

	CAPM β						CAPM α (% p.a.)					
	Industry β is:						Industry β is:					
Stock β is:	**Low**	**2**	**3**	**4**	**High**	**Low – High**	**Low**	**2**	**3**	**4**	**High**	**Low – High**
Panel A. Point estimates												
Low	0.54	0.71	0.72	0.68	0.87	–0.34	2.71	3.87	–2.17	–1.57	1.79	0.92
2	0.70	0.80	0.78	0.82	0.93	–0.23	2.91	3.31	–0.14	–1.09	4.28	–1.37
3	0.88	0.96	0.97	0.99	1.11	–0.22	0.57	3.21	–0.80	1.37	0.11	0.47
4	1.24	1.15	1.21	1.20	1.29	–0.05	0.59	0.89	–2.30	–1.29	–1.51	2.10
High	1.48	1.46	1.48	1.55	1.64	–0.16	0.92	–2.32	–7.88	–3.71	–4.61	5.54
Low – High	–0.94	–0.75	–0.76	–0.88	–0.76		1.78	6.19	5.71	2.14	6.40	
Industry effect (average of Low – High column)						–0.20						1.53
Within-industry effect (average of Low – High row)						–0.82						4.44
Total effect												5.97
Panel B. *t*-statistics												
Low	20.34	25.61	20.45	19.27	21.31	–6.78	1.84	2.51	–1.11	-0.8	0.78	0.33
2	29.42	36.87	31.11	26.78	33.06	–6.23	2.18	2.73	–0.10	-0.63	2.71	-0.66
3	36.16	44.38	42.95	40.56	48.49	–7.04	0.42	2.64	-0.63	1.01	0.08	0.27
4	36.67	43.82	49.85	44.76	52.77	–1.26	0.31	0.61	–1.70	–0.86	–1.10	0.91
High	27.82	34.35	40.26	40.51	41.85	–2.61	0.31	–0.98	–3.83	–1.73	–2.11	1.66
Low – High	–16.54	–15.77	–16.15	–17.72	–14.56		0.56	2.31	2.16	0.77	2.19	
Industry effect (average of Low – High column)						–6.71						0.92
Within-industry effect (average of Low – High row)						–24.93						2.42

Table 5. CAPM betas and annualized alphas for portfolios formed on prior 60-week country betas, developed markets 1989-2012. At the beginning of each month, we use quintile breakpoints to assign each stock in the S&P Broad Market Index (BMI) developed markets database to a portfolio based on its country beta. Country betas are the capitalization-weighted averages of constituent stocks' betas, which are estimated using the prior 60 weeks (minimum 12 weeks) of returns, where all returns are measured in U.S. dollars. For each set of breakpoints, we capitalization-weight the stocks in the resulting five portfolios, and we regress each portfolio's monthly excess returns on a constant and the market excess returns to find full-period *ex post* CAPM betas (left columns) and alphas (right columns). Panel A reports point estimates for the regressions, and Panel B reports corresponding *t*-statistics. Observation window is November 1989 through December 2012.

	CAPM β	CAPM α (% p.a.)
	Portfolios formed on:	Portfolios formed on:
	Country β	Country β
Panel A. Point estimates		
Low	0.77	5.87
2	0.86	4.77
3	0.99	0.78
4	1.12	–1.49
High	1.32	–0.99
Low – High	–0.55	6.86
Panel B. *t*-statistics		
Low	21.71	2.97
2	27.05	2.68
3	31.81	0.45
4	33.49	–0.80
High	30.15	–0.41
Low – High	–8.78	1.97

Table 6. CAPM betas and annualized alphas for portfolios formed jointly on prior 60-week betas and prior 60-week country betas, developed markets 1989-2012. At the beginning of each month, we use independent quintile breakpoints to assign each stock in the S&P Broad Market Index (BMI) developed markets database to a portfolio based on its own beta and its country beta, where stock betas are estimated using the prior 60 weeks (minimum 12 weeks) of returns and country betas are the capitalization-weighted averages of the betas of constituent stocks, and where all returns are measured in U.S. dollars. We capitalization-weight the stocks in the resulting 25 portfolios, and we regress each portfolio's monthly excess returns on a constant and the market excess returns to find full-period *ex post* CAPM betas (left columns) and alphas (right columns). Panel A reports point estimates for the regressions, and Panel B reports corresponding *t*-statistics. Observation window is November 1989 through December 2012.

	CAPM β						CAPM α (% p.a.)					
	Country β is:						Country β is:					
Stock β is:	**Low**	**2**	**3**	**4**	**High**	**Low – High**	**Low**	**2**	**3**	**4**	**High**	**Low – High**
Panel A. Point estimates												
Low	0.52	0.52	0.64	0.62	0.65	–0.13	5.49	6.27	1.97	0.16	–3.62	9.11
2	0.74	0.71	0.79	0.83	0.78	–0.04	7.55	6.77	3.51	0.71	–2.94	10.48
3	0.97	0.88	0.96	0.99	0.93	0.03	2.68	6.94	2.29	0.60	0.09	2.59
4	1.17	1.1	1.14	1.19	1.09	0.08	2.60	2.00	0.11	–2.35	–0.69	3.29
High	1.62	1.59	1.62	1.51	1.67	–0.06	0.87	–0.39	–3.73	–8.71	–4.74	5.61
Low – High	–1.09	–1.07	–0.98	–0.89	–1.02		4.62	6.66	5.7	8.88	1.11	
Country effect (average of Low – High column)						–0.02						6.22
Within-country effect (average of Low – High row)						–1.01						5.40
Total effect												11.61
Panel B. *t*-statistics												
Low	14.35	12.29	13.27	12.62	10.41	–1.94	2.71	2.7	0.74	0.06	–1.04	2.45
2	18.87	19.40	21.71	18.83	15.77	–0.78	3.47	3.33	1.74	0.29	–1.07	3.43
3	21.58	21.79	28.00	25.07	19.94	0.54	1.08	3.11	1.21	0.27	0.04	0.73
4	19.17	22.63	32.45	30.56	23.93	1.07	0.77	0.74	0.06	–1.09	–0.27	0.78
High	15.39	21.62	26.71	23.22	27.52	–0.50	0.15	–0.10	–1.11	–2.41	–1.40	0.88
Low – High	–10.08	–12.75	–13.74	–12.01	–12.98		0.77	1.43	1.45	2.16	0.26	
Country effect (average of Low – High column)						–0.42						2.04
Within-country effect (average of Low – High row)						–17.95						1.73

Table 7. CAPM betas and annualized alphas for portfolios formed jointly on prior 60-month idiosyncratic volatility and prior industry and country idiosyncratic volatility. Panels A and B repeat the analysis in Tables 4 and 6, respectively, using the volatility of the residual from the CAPM regressions described there, instead of the beta. Specifically, at the beginning of each month, we use independent quintile breakpoints to assign each stock in the CRSP (BMI) database to a portfolio based on its own idiosyncratic volatility and its industry (country) idiosyncratic volatility, where stocks' idiosyncratic volatiles are estimated using the prior 60 months (weeks) of returns and industry (country) idiosyncratic volatiles are the capitalization-weighted averages of the idiosyncratic volatiles of their constituent stocks. We capitalization-weight the stocks in the resulting 25 portfolios, and we regress each portfolio's monthly excess returns on a constant and the market excess returns to find full-period *ex post* CAPM betas (left columns) and alphas (right columns). We report the average differences between low and high idiosyncratic risk industries (countries) controlling for stock-level idiosyncratic risk as the "industry effect" ("country effect"), and we report the average differences between low and high idiosyncratic risk stocks controlling for industry (country) idiosyncratic volatility as the "within-industry" ("within-country") effect. Estimation window is 1968-2012 (CRSP, Panel A) and 1989-2012 (BMI, Panel B).

	CAPM β		CAPM α (% p.a.)	
	Point Estimate	**T-Stat**	**Point Estimate**	**T-Stat**
Panel A. CRSP Sample				
Industry effect	–0.22	–6.31	0.42	0.22
Within-industry effect	–0.73	–14.39	10.21	3.59
Total effect			10.63	
Panel B. BMI Sample				
Country effect	0.03	0.43	1.54	0.42
Within-country effect	–0.78	–12.66	9.72	2.82
Total effect			11.26	