Betting Against Correlation: Testing Theories of the Low-Risk Effect

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Abstract

We test whether the low-risk effect is driven by (a) leverage constraints and thus risk should be measured using beta vs. (b) behavioral effects and thus risk should be measured by idiosyncratic risk. Beta depends on volatility and correlation, where only volatility is related to idiosyncratic risk. We introduce a new betting against correlation (BAC) factor that is particularly suited to differentiate between leverage constraints vs. lottery explanations. BAC produces strong performance in the US and internationally, supporting leverage constraint theories. Similarly, we construct the new factor SMAX to isolate lottery demand, which also produces positive returns. Consistent with both leverage and lottery theories contributing to the low-risk effect, we find that BAC is related to margin debt while idiosyncratic risk factors are related to sentiment.

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1. Introduction

The relation between risk and expected return is a central issue in finance with broad implications for investment behavior, corporate finance, and market efficiency. One of the major stylized facts on the risk-return relation, indeed in empirical asset pricing more broadly, is the observation that assets with low risk have high alpha, the so-called "low-risk effect" (Black, Jensen, and Scholes, 1972).[1] However, the literature offers different views on the underlying economic drivers of the low-risk effect and the best empirical measures. In short, the debate is whether (a) the low-risk effect is driven by leverage constraints and risk should be measured using systematic risk vs. (b) the low-risk effect is driven by behavioral effects and risk should be measured using idiosyncratic risk.[2] This paper seeks to test these theories using broad global data, controlling for more existing factors, using measures of the economic drivers, and using new factors that we call betting against correlation (BAC) and scaled MAX (SMAX) that help solve the problem that the existing low-risk factors are highly correlated.

The theory of leverage constraints for the low-risk effect was proposed by Black (1972) and extended by Frazzini and Pedersen (2011, 2014) who study an extensive set of global stocks, bonds, credits, and derivatives based on their betting against beta (BAB) factor. Hence, the systematic low-risk effect is based on a rigorous economic theory and has survived more than 40 years of out of sample evidence. Further, a number of papers document evidence consistent with the underlying economic mechanism of leverage constraints: Jylhä (2015) finds that exogenous changes in margin requirements influence the slope of the security market line, Boguth and

[1] We use the standard term "low-risk effect" to refer to the (risk-adjusted) return spread between low- and high-risk stocks (i.e., it does not just refer to low-risk stocks).

[2] A related but distinct debate is whether other factors subsume low-risk factors or vice versa (see, for instance, Novy-Marx, 2014 and Fama and French, 2016) and we also address this debate herein as discussed below. We note however, that BAB and BAC are based on equilibrium theories of asset pricing while the other factors are ad hoc empirical specifications.

Simutin (2014) show that funding constraints as proxied by mutual fund beta predict BAB, Malkhozov, Mueller, Vedolin, and Venter (2016) show that international illiquidity predict BAB, and Adrian, Etula, and Muir (2014) document a strong link between the return to BAB and financial intermediary leverage.[3]

The alternative view is that the low-risk effect stems from behavioral biases leading to a preference for lottery-like returns (Barberis and Huang, 2008; Brunnermeier, Gollier, and Parker, 2007) and therefore the focus should be on idiosyncratic risk. Indeed, Ang, Hodrick, Xing, and Zhang (2006, 2009) find that stocks with low idiosyncratic volatility (IVOL) have high risk-adjusted returns in the U.S. and internationally. In a similar vein, Bali, Cakici, and Whitelaw (2011) consider stocks sorted on the maximum return (MAX) over the past month, finding that low MAX is associated with high risk-adjusted returns, [4] and Bali, Brown, Murray, and Tang (2016) argue that the low-risk effect is driven by idiosyncratic risk rather than systematic risk. Also, Liu, Stambaugh, and Yuan (2017) argue that the low-risk effect is driven by idiosyncratic risk and only appears among over-priced stocks.

The challenge with the existing literature is that it seeks to run a horse race between factors that are, by construction, highly correlated since risky stocks are usually risky in many ways. Indeed, the reason that all these factors are known under the umbrella term "the low-risk effect" is that they are so closely related. Hence, the most powerful way to credibly distinguish these theories is to construct a new factor that captures one theory while at the same being relatively unrelated to factors capturing the alternative theory. To accomplish this, we decompose BAB into two factors: betting against correlation (BAC) and betting against volatility

[3] See also the related evidence on corporate finance and banking (Baker and Wurgler, 2015, 2016), benchmark constraints (Brennan, 1993; Baker, Bradley, and Wurgler, 2011) and leverage constraints and differences of opinion (Hong and Sraer, 2015).
[4] See also the measure related to idiosyncratic skewness studied by Boyer, Mitton, and Vorkink (2009).

(BAV). BAC goes long stocks that have low correlation to the market and shorts those with high correlation, while seeking to match the volatility of the stocks that are bought and sold. Likewise, BAV goes long and short based on volatility, while seeking to match correlation. This decomposition of BAB creates a component that is relatively unrelated to the behavioral factors (BAC) and a closely related component (BAV). To see that BAC is relatively unrelated to the behavioral-based factors, we note that the long and short sides of BAC have similar average volatility, skewness, and MAX.[5] At the same time, sorting on ex ante market correlation successfully creates a BAC factor that is long stocks with low ex post market correlations (and short stocks with high ones).

Since stocks with low market correlation have low market betas, the theory of leverage constraints implies that BAC has positive risk-adjusted returns, just like BAB. Empirically, we find that BAC is about as profitable as the BAB factor and BAC has a highly significant CAPM alpha as predicted by the theory of leverage constraints. This evidence thus supports the theory of leverage constraints and is clearly separate from the behavioral factors.

To address the findings of Liu, Stambaugh, and Yuan (2017), we double-sort on their measure of each stock's "mispricing" and our measure of each stock's correlation with the market, finding that low-correlation stocks deliver higher risk-adjusted returns in each quintile of mispricing, providing further evidence that the low-risk effect is not just about idiosyncratic risk or its interaction with mispricing. At the same time, mispricing predicts stock returns controlling for correlation, so leverage constraints do not explain all anomalies – there appears to be a separate role for other effects as considered by Liu, Stambaugh, and Yuan (2017).

[5] The volatility is matched by construction and the MAX characteristic is matched due to its close relation to volatility. Indeed, the average MAX characteristics of the stocks in the long and short leg of BAC are 0.039 and 0.037, i.e., a small difference relative to the average cross-sectional standard deviation of MAX of 0.032.

Another challenge to the low-risk effect, both with systematic and idiosyncratic risk, is posed by Fama and French (2016) who argue that that a five-factor model of the market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA) explains the low-risk effect (and the majority of the cross-section of returns more broadly, except for momentum). While they don't test BAB explicitly, they suggest that there is no relationship between alpha and systematic risk once controlling for the five factors. We study this question explicitly and, further, we also control for short-term reversal (REV), which is particularly relevant for the idiosyncratic risk factors (due to their high turnover as discussed below). We find significant alpha for BAB and BAC for a variety of combinations of control factors in the US and globally. For example, BAC has a five-factor alpha of 0.7% per month (*t*-statistic of 5.5) in the U.S and 0.37% in our global sample (*t*-statistic of 2.8).

Turning to the behavioral theory, we next consider the factors that go long stocks with low MAX return (LMAX) or low idiosyncratic volatility (IVOL). We sign all factors such that they are long low-risk stocks (even though the literature is not always consistent in this regard).[6] Since IVOL is already based on decomposing volatility into its systematic and idiosyncratic parts, we do not further decompose IVOL. For LMAX, however, we can again create a new factor that helps differentiate alternative hypotheses by removing the common component (namely, volatility). Just like we created BAC to remove the effect of volatility from beta (which left us with correlation), we can remove the effect of volatility from MAX: We construct a scaled-MAX (SMAX) factor that goes long stocks with low MAX return divided by ex ante volatility and shorts stocks with the opposite characteristic. This factor captures lottery demand

[6] For example, LMAX is the negative of the FMAX factor considered by Bali, Cakici, and Whitelaw (2011).

in a way that is not as mechanically related to volatility as it is more purely about the *shape* of the return distribution.

Behavioral theories imply that these idiosyncratic risk factors should have positive alphas, which we confirm in the data. In the U.S., SMAX, LMAX, and IVOL all produce significant alphas with respect to the Fama-French five-factor model, but SMAX performs stronger than both LMAX and IVOL. In the global sample, however, none of the factors are robust to controlling for the five Fama-French factors and short-term reversal.

To go beyond studying the risk-adjusted returns, we study additional predictions arising from the different economic theories for the low-risk effect. To capture the idea underlying the theory of leverage constraints, we consider the margin debt held by customers at NYSE member organizations (broker-dealers). To capture the behavioral effects, we consider investor sentiment as suggested by Liu, Stambaugh, and Yuan (2017). We find that BAB and BAC are predicted by measures of leverage constraints, while these factors are not predicted by investor sentiment. In contrast, MAX and IVOL are (weakly) related to sentiment, but not measures of leverage constraints. This evidence is consistent with both of the alternative theories playing a role and that the alternative factors may, to some extent, capture different effects.[7]

To study behavioral lottery demand more directly, we consider two new measures of lottery demand: profits earned by casinos in the U.S. and sales of lottery tickets in the UK. We find that the predictive power of casino profits for LMAX and IVOL is insignificant. However, a contemporaneous increase in casino profits is associated with low returns to LMAX and IVOL,

[7] We also consider other alternative theories of the low-risk effect. In particular, the literature also includes so-called Money Illusion as suggested by Modigliani and Cohn (1979) and studied by Cohen, Polk, and Vuolteenaho (2005). However, we find no evidence that inflation predicts either BAB or BAC. This result holds despite the fact that we include the 70's and 80's, time periods that included large shocks to inflation.

consistent with theories of lottery demand. We find no evidence, however, that higher sales of lottery tickets is associated with the profits of any of the "lottery factors", neither predictive nor contemporaneously. Finally, we find that BAB and BAC are not associated with casino profits or lottery sales, consistent with these factors being driven by leverage constraints and not lottery demand.

Having tested the specific predictions arising from the competing theories of the leverage effect, we next run "horseraces" between the different low-risk factors to judge their relative importance. We regress each type of low-risk factor (systematic/idiosyncratic) on the alternate type of low-risk factor as well as several controls (the Fama-French factors and short-term reversal). We find that BAB and BAC are robust to controlling for LMAX and IVOL in the US and globally. Turning things around, we find that SMAX is robust to controlling for BAB in the US, but LMAX and IVOL both have insignificant alphas when we control for BAB (recall that the behavioral factors were insignificant globally even before we control for BAB).

These insignificant alphas of the idiosyncratic risk factors arise because their returns are captured by BAB and our control variables. Indeed, controlling for profitability lowers the alpha as documented by Novy-Marx (2014) and so does controlling for short-term reversal (REV), which is natural since both the IVOL and MAX characteristics are computed over the last month like REV and, hence, may be partly driven by microstructure effects. Controlling for BAB further lowers their alphas. The insignificant alphas may not, however, rule out that lottery demand matters since we are controlling for many factors, some of which could themselves capture similar effects.

Finally, we address that the different factors we have considered are based on different construction methods. BAB, BAC, and BAV are rank-weighted while the other factors are constructed using the Fama and French (1993) methodology. Further, the LMAX, SMAX, and IVOL characteristics are calculated over only a single month and the factors thus have much higher turnover than typical factors that capture a more stable stock characteristic (e.g., BAB, BAC, or the Fama-French factors). To address these differences, we run apples-to-apples regressions where we construct all factors using the same method and, in some cases, we also slow down the turnover of the MAX characteristic by calculating it over a longer period. We find that the systematic-risk factors are relatively robust across apples-to-apples regressions, while the idiosyncratic-risk factors appear less robust, especially with respect to formation periods because the alphas of LMAX and SMAX are almost exclusively associated with the month after the characteristics is calculated.

In summary, we find that BAB and BAC are robust to controlling for a host of other factors, have survived significant out-of-sample evidence – both through time and across asset classes and geographies – have lower turnover than many of the well-known idiosyncratic-risk measures, making them more implementable and realistic, and are supported by rigorous theory of leverage constraints with consistent evidence based on margin debt. Turning to the factors based on idiosyncratic risk, we note that these are more often defined based on a relatively short time period (high turnover) making them susceptible to microstructure noise and making it harder to believe that they capture the idea underlying the behavioral theory,[8] they are less robust to controlling for other factors and to using a lower turnover, and they are weaker globally. The

[8] If behavioral investors naively look for lottery stocks, then perhaps the simplest way to do so would be to buy stocks from industries with high skewness. However, the MAX factor does not work for industry selection (see appendix). In contrast, Asness, Frazzini, and Pedersen (2014) find that BAB works both within and across industries.

strongest version appears to be our new SMAX factor, which is related to measures of sentiment. The low-risk effect can be driven by more than one economic effect and the evidence is not inconsistent with both leverage constraints and lottery demand playing a role.

2. Data and Methodology

Our sample consists of 58,415 stocks covering 24 countries between January 1926 and December 2015. The 24 markets in our sample correspond to the countries belonging to the MSCI World Developed Index as of December 31, 2012. We report summary statistics in Table I. Stock returns are from the union of the CRSP tape and the XpressFeed Global Database. All returns are in USD and do not include any currency hedging. Since all returns are in USD, all excess returns are measured as excess returns above the U.S. Treasury bill rate.[9]

We divide stocks into a long U.S. sample and a broad global sample. The U.S. sample consists of all available common stocks on the CRSP tape from January 1926 to December 2015. For each regression, we use the longest available sample depending on the availability of relevant factors, where some factors are only available from 1964 and onwards.

Our broad global sample contains all available common stocks on the union of the CRSP tape and the XpressFeed Global database. Table I contains the start date of the data in each country, but all regressions are from July 1990, the starting data of the global Fama-French factors, to December 2015. For companies traded in multiple markets, we use the primary trading vehicle identified by XpressFeed.

2.1. Constructing BAC and BAV factors

[9] Said differently, we consider the return to converting USD 1 into foreign currency, investing in foreign stocks, and then next time period converting the proceeds back to USD, in excess of simply investing in US T-Bills.

We construct betting against correlation portfolios in each country in the following way. At the beginning of each month, stocks are ranked in ascending order based on the estimate of volatility at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are ranked based on the estimate of correlation at the end of the previous month and assigned to one of two portfolios: low correlation and high correlation. In these portfolios, stocks are weighted by ranked correlation (lower correlation stocks have larger weights in the low-correlation portfolios and larger correlation stocks have larger weights in the high-correlation portfolios), and the portfolios are rebalanced every calendar month. Both portfolios are (de)levered to have a beta of one at formation. Within each volatility quintile, a self-financing BAC portfolio is constructed to go long the low-correlation portfolio and short the high-correlation portfolio. Our overall BAC factor is then the equal-weighted average of the five betting against correlation factors.

More formally, let z^q be the $n(q) \times 1$ vector of correlation ranks within each volatility quintile $q = 1,2,3,4,5$ and $\overline{z^q} = 1'_{n(q)} z^q / n(q)$ be the average rank, where $n(q)$ is the number of securities in volatility quintile q and $1_{n(q)}$ is an $n(q) \times 1$ vector of ones. The portfolio weights of the high-correlation and the low-correlation portfolios in each volatility quintile are then given by

$$w_H^q = k^q (z^q - \overline{z^q})^+$$

$$w_L^q = k^q (z^q - \overline{z^q})^-$$

where k^q is a normalizing constant $k^q = 2/1'_{n(q)}|z^q - \overline{z^q}|$ and x^+ and x^- indicate the positive and negative elements of a vector x. By construction, we have $1'_{n(q)}w_H^q = 1$ and $1'_{n(q)}w_L^q = 1$. The excess return to BAC in each volatility quintile is then

$$r_{t+1}^{BAC(q)} = \frac{1}{\beta_t^{L,q}}\left(r_{t+1}^{L,q} - r^f\right) - \frac{1}{\beta_t^{H,q}}\left(r_{t+1}^{H,q} - r^f\right)$$

Here, r^f is the risk-free return, $r_{t+1}^{L,q} = r_{t+1}^{q\prime}w_L^q$ and $r_{t+1}^{H,q} = r_{t+1}^{q\prime}w_H^q$ are the returns of the low- and high-correlation portfolios, and $\beta_t^{L,q} = \beta_t^{q\prime}w_L^q$, and $\beta_t^{H,q} = \beta_t^{q\prime}w_H^q$ are the corresponding betas. The return to the final BAC factor is given by

$$r_{t+1}^{BAC} = \frac{1}{5}\sum_{q=1}^{5} r_{t+1}^{BAC(q)}$$

Betting against volatility is constructed similarly to BAC, only stocks are first sorted into quintiles based on correlation instead of volatility:

$$r_{t+1}^{BAV} = \frac{1}{5}\sum_{q=1}^{5} r_{t+1}^{BAV(q)}$$

The global BAC factors are the average of the national portfolios in the sample weighted by their ex-ante market capitalization.

$$r_{t+1}^{BAC,global} = \sum_{k=1}^{K} \frac{\pi_t^k}{\sum_j \pi_t^j} r_{t+1}^{BAC,k}$$

$$r_{t+1}^{BAV,global} = \sum_{k=1}^{K} \frac{\pi_t^k}{\sum_j \pi_t^j} r_{t+1}^{BAV,k}$$

where π_t^k is the market capitalization of country k at time t.

To construct BAC and BAV factors, we need to estimate beta, correlation, and volatility for all stocks. We estimate beta as in Frazzini and Pedersen (2014):

$$\hat{\beta}_i^{TS} = \hat{\rho}_{i,m} \frac{\hat{\sigma}_i}{\hat{\sigma}_m}$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities of stock i and the market m and $\hat{\rho}_{i,m}$ is the estimated correlation. To estimate correlation, we use a five-year rolling windows of overlapping three-day[10] log-returns, $r_{i,t}^{3d} = \sum_{k=0}^{2} \ln(1 + r_{t+k}^i)$. Volatilities are estimated using one-year rolling windows of one-day log-returns. We require at least 750 trading days of non-missing return data to estimate correlation and 120 trading days of non-missing return data to estimate volatility. Finally, we shrink the time-series estimate of betas towards their cross-sectional mean, $\hat{\beta}_i = w_i \hat{\beta}_i^{TS} + (1 - w_i)\beta^{XS}$, where TS stands for beta estimated for each stock using its time-series of returns and XS stands for the cross-sectional mean beta (using the method of Vasicek, 1973). Specifically, we use a shrinkage factor of $w_i = 0.6$ and cross-sectional mean $\beta^{XS} = 1$. The choice of shrinkage factor does not affect the sorting of the portfolios, only the amount of leverage applied.

2.2. Constructing LMAX, SMAX, and IVOL factors

[10] We use 3-day overlapping returns to estimate correlations to account for non-synchronous trading.

To capture the behavioral explanations of the low-risk effect, we construct LMAX, SMAX, and IVOL factors. First, we consider the LMAX factor. The LMAX factor is the negative of the FMAX factor introduced by Bali, Brown, Murray, and Tang (2016) to ensure that all factors are long low-risk stocks. Specifically, LMAX is long stocks with low MAX and short stocks with high MAX, where MAX is the average of the five highest daily returns over the last month.

We construct an LMAX factor in each country and a global LMAX factor, which is the average of the country-specific LMAX factors weighted by each country's market capitalization π_t^k:

$$r_{t+1}^{LMAX,global} = \sum_{k=1}^{K} \frac{\pi_t^k}{\sum_j \pi_t^j} r_{t+1}^{LMAX,k}$$

The country-specific LMAX portfolios are constructed as the intersection of six value-weighted portfolios formed on size and MAX. For U.S. securities, the size breakpoint is the median NYSE market equity. For international securities, the size breakpoint is the 80th percentile by country. The MAX breakpoints are the 30th and 70th percentile. We use unconditional sorts in the U.S. and conditional sorts in the international sample as many countries do not have a sample size that makes unconditional sorts useful (first we sort on size and then MAX). Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. LMAX is the average of the low-MAX/large-cap and low-MAX/small-cap portfolio returns minus the average of the high-MAX/large-cap and high-MAX/small-cap portfolio returns.

Just as beta is the product of correlation and volatility, a stock can have a high MAX because of high volatility or high positive skewness. To decompose these effects, we construct a scaled MAX (SMAX) as follows. For each stock, we compute the average of the five highest daily returns over the last month, divided by the stock's volatility (estimated as described in Section 2.1). We then compute the SMAX factor exactly as above just based on this scaled MAX characteristic rather than the standard MAX.

Lastly, we construct IVOL factors based on the characteristic used in Ang, Hodrick, Xing, Zhang (2006). To estimate idiosyncratic volatility, we regress each firm's daily stock returns over the given month on the daily returns to the market, size, and value factors. The residual volatility in this estimation is our measure of idiosyncratic volatility for the given firm in the given month. In the U.S., we follow Ang, Hodrick, Xing, and Zhang (2006) and use the market, size, and value portfolios of Fama and French (1993) as right-hand-side variables and, outside the U.S., we use the factor portfolios of Asness and Frazzini (2013). Based on these estimated characteristics, the IVOL factor is constructed in the same way as the LMAX and SMAX factors. The IVOL factor is long low-IVOL stocks and short high-IVOL stocks.

2.3. *Explanatory variables in factor regressions*

We use the Fama and French factors (1993, 2015) whenever available. In particular, we use their 5-factor model based on the value-weighted market factor (MKT), size factor small-minus-big (SMB), value factor high-minus-low (HML), profitability factor robust-minus-weak (RMW), and investment factor conservative-minus-aggressive (CMA). We also use their short-term reversal factor (REV).

2.4. *Economic variables*

We construct our leverage measure based on the amount of margin debt held by customers at NYSE member organizations (broker-dealers). The data is available from 1959-2015 and it is published on the NYSE website.[11] At the end of each month, we calculate the ratio of margin debt to the market capitalization of NYSE stocks which constitute our margin debt (MD) measure:

$$MD_t = \frac{\text{Margin debt}_t}{\text{Market capitalization of NYSE firms}_t}$$

To capture investor sentiment, we use the sentiment index by Baker and Wurgler (2006). As inflation measure, we use the yearly change in the consumer price index from the FRED database.

We introduce two new measures of lottery demand. The first measure is a measure of casino profits in the U.S. The measure is the quarterly time-series of profits for the Casino industry scaled by nominal GDP. The casino industry has the North American Industry Classification Code (NAICS) 713210. We measure profits as revenue (REVTQ in Compustat) minus cost of goods sold (COGSQ in Compustat). We correct for seasonality using the X11 procedure.

The second measure of lottery demand is based on sales in the UK state lottery. Each month, we aggregate the total sales in the UK state lottery, which takes place every Wednesday and Saturday starting in 1993. These total monthly sales divided by UK nominal GDP constitute our UK lottery factor.[12] We again correct for seasonality using the X11 procedure. Throughout the analysis, we use UK factors on the right-hand side whenever we have the UK lottery measure on the right hand side.

3. Systematic Risk: Betting Against Correlation, Volatility, and Beta

In this section, we dissect the betting against beta factor into a betting against correlation factor and a betting against volatility factor. The idea is to decompose BAB into two components: one component, BAV, that is more closely linked to idiosyncratic volatility and MAX and another

[11] The data can be found on
http://www.nyxdata.com/nysedata/asp/factbook/viewer_edition.asp?mode=table&key=3153&category=8

[12] The data can be found on http://lottery.merseyworld.com/Sales_index.html.

component, BAC, with little relation to these alternative factors. BAV is a pure volatility bet and BAC is a pure bet against systematic risk.

The theory of leverage constraints of Black (1972) and Frazzini and Pedersen (2014) implies that stocks with higher betas have lower risk-adjusted returns regardless of whether the high beta arises from high volatility or high market correlation. Hence, this theory predicts that both components of BAB, BAC and BAV, should deliver positive alphas.

3.1. Double-sorting on correlation and volatility

Before we consider the actual factors, we consider a simple double sort of volatility and correlation. Table II shows risk-adjusted returns for 25 portfolios sorted first on volatility and then conditionally on correlation. In each row, all portfolios have approximately the same volatility, but increase in correlation from the left column to the right column.

Panel A considers whether sorting on ex ante volatility and correlation successfully sorts on ex post market beta. Indeed, as correlation is often considered more difficult to estimate than volatility, it is important to consider whether the ex ante estimate predicts future systematic risk. As seen in the table, ex post CAPM beta does increase with both ex ante correlation and ex ante volatility. In fact, sorting on correlation and volatility produce similar magnitudes of spreads in ex post betas. Since stocks with higher correlation (and the same volatility) have larger betas, the theory of leverage constraints implies that these stocks have lower alphas (and similarly for stocks with higher volatility and the same correlation).

Table II Panel B and C next consider the risk-adjusted returns for these portfolios. We see that both the CAPM alpha (Panel B) and the three-factor alpha (Panel C) decrease as correlation or volatility increase. To examine the economic and statistical significance of these results, we consider the long/short portfolios in, respectively, the rightmost column and the bottom row. We see that the separate effects of volatility and correlation on risk-adjusted returns are significant for many of the cases, with the effect of correlation appearing especially strong.

3.2. Decomposing BAB into BAC and BAV

We next turn to the study of the long-short factors constructed as described in Section 2. Given that market betas can be decomposed into market correlation and volatility, we first show how BAB can be decomposed into BAC and BAV:

$$BAB_t = a_0 + a_1 BAC_t + a_2 BAV_t + \varepsilon_t$$

Table III reports the result, showing that both BAC and BAV contribute to the return of the original BAB factor. In the U.S., BAB has a loading of 0.71 on BAC and 0.51 on BAV, while the loadings in the global sample are 0.84 and 0.49. The *R*-squared of the regressions are 85% in the U.S. sample and 96% in the global sample. Both of the intercepts are statistically indifferent from zero.

3.3. The performance and factor loadings of BAC

We next focus on the performance of the key new factor, BAC. Table IV reports the return and factor loadings of the BAC factor and its building blocks. Recall that we construct betting against correlation factors within each volatility quintile and then the overall BAC factor is the equal-weighted average of these five factors. Panel A shows the results in the U.S., and we see that BAC has a statistically significant alpha with respect to the Fama-French 5-factor model within each volatility quintile as well as for the overall BAC factor.

Panel B in Table IV reports the analogous results in the global sample. We see that the overall BAC factor has a positive and statistically significant alpha. Also, the BAC factors within each volatility quintile have positive alphas, but they are not all statistically significant.

Turning to the factor loadings, we see that the overall BAC factor has a beta close to zero, suggesting that the ex-ante market hedge works as intended. Further, the overall BAC factor loads substantially on the small-minus-big factor as firms with, for the same volatility, low correlation often are small, undiversified firms. The BAC factor has a positive loading on the value factor (HML), consistent with the theory of leverage constraints. Indeed, the theory of leverage constraints predicts that safe stocks, those with low correlation and volatility, become cheap because they are "abandoned" by leverage constrained investors, giving rise to a positive HML loading. Lastly, we see that the loadings on RMW and CMA also tend to be positive, especially those of RMW. This is also expected since, as noted by Asness, Frazzini, and Pedersen (2013), all these are measures of quality and safety. Said differently, a stock's safety can be measured based on price data or accounting data and it is not surprising that these measures are related.

Given that the Fama-French factors (other than the MKT) have little theoretical foundation and given that the return of these factors is consistent with the theory of leverage constraints, controlling for these factors is arguably too stringent of a test.[13] Indeed, the theory of leverage constraints predicts that BAB and BAC produce positive CAPM alphas, but this theory does *not* predict that these factors produces positive alphas relative to right-hand-side variables

[13] In principle if book-to-price was a perfect measure of "value" then the BAB factor would be fully explained by HML under the theory of leverage constraints. One interpretation based on the theory of leverage constraints, is that low beta stocks tend to be cheaper due to leverage constraints, and because we do not have near a perfect measure of cheapness, the beta itself helps measure it. Said another way, both low book-to-price and low beta are noisy measures of "value." Of course, value effects may also be explained by effects other than leverage constraints as we discuss further in Section 5.2.

that capture the same idea. All that said, it is all the more impressive that the alpha of BAC remains significant when controlling for the 5 factors, which reflects that these factors are sufficiently different in their content and construction.

Given the positive factor loadings, we could also turn the regression around and conclude that BAC and, more broadly, the theory of leverage constraints, could partly explain these Fama-French factors.

The performance of BAV is less interesting for our purposes since it is close to the factors in the literature by construction. However, for completeness, we present similar factor regressions for the BAV factor in appendix Tables A1 and A2 (see also Table VI below). In the U.S., BAV produces positive and statistically significant CAPM- and three-factor alphas, but its five-factor alpha is insignificant as are the alphas in the global sample. One striking difference in factor loadings between BAC and BAV is on small-minus-big. Where low correlation stocks, holding volatility constant, tend to be small stocks, low volatility stocks, holding correlation constant, tend to be big stocks.

In summary, BAB – and especially its purely systematic component BAC – appears robust across a variety specifications and control variables. In appendix tables A3-A4, we document that the results are robust to using other measures of correlation and market beta, such as the beta measures used by Fama and French (1992). Sorting stocks based on the correlation implied by beta measure of Fama and French (1992) results in a smaller ex post beta spread, but the effect on alpha remains statistically significant. In section 5, we test if the economic drivers of this systematic part, but, before doing so, we analyze the robustness of the idiosyncratic part of the low-risk effect.

4. Idiosyncratic Risk: LMAX, SMAX, and IVOL

In this section, we analyze the robustness of the empirical observations that stocks with high idiosyncratic volatility and lottery-like returns have low alpha. By idiosyncratic volatility, we refer to the idiosyncratic volatility characteristic defined by Ang, Hodrick, Xing, Zhang (2006), which is the monthly residual volatility in the Fama-French three-factor model as explained in our methodology section. By lottery-like we again refer to the MAX characteristic (Bali, Cakici, and Whitelaw 2011), which is the mean of the five highest daily returns over the last month as explained in our methodology section, and our new factor SMAX.

4.1. Double-sorting on MAX and volatility

A stock can have a high MAX return either because it is volatile or because its return distribution is right-skewed. To draw this distinction, we consider each stock's scaled maximum return, that is, its MAX return divided by its ex ante volatility. This measure captures a stock's realized return distribution. An investor who does not face leverage constraints but seeks lottery-like returns can apply leverage to a stock with low volatility and high scaled MAX. Hence, scaled MAX isolates what's different about the lottery demand.

Table V shows CAPM and three factor alphas of 25 portfolios sorted first on volatility and then conditionally on scaled MAX. We see that scaled MAX is associated with significant alpha, even when keeping volatility constant.

4.2. Decomposing LMAX into SMAX and BAV

We next turn to the LMAX factor that goes long stocks with low MAX returns while shorting those with high MAX. The results in Section 4.1 suggest that LMAX gets its alpha both from betting against high volatility and from betting against stocks with high scaled max. Table VI formally decomposes LMAX into the factor that goes long stocks with low scaled max

(SMAX) and the factor that goes long stocks with low total volatility over the past month (TV). Both in the U.S. and globally, the two factors combine to explain most of the variation in LMAX; the R-squared is 90 percent in the U.S. and 97 percent globally with insignificant intercepts.

4.3. The performance of idiosyncratic risk factors: LMAX, SMAX, and IVOL

Table VII reports the performance and factor exposures of the three idiosyncratic risk factors. The three factors have almost identical three-factor alpha and three-factor information ratios. All three factors remain significant when we also control for RMW, CMA, and REV, but the alpha of SMAX is statistically more robust than LMAX and IVOL in the sense that the six-factor *t*-statistic is more significant for SMAX.

Turning to the factor loadings, we see that the idiosyncratic risk factors tend to load on the quality variables RMW and CMA. Also, LMAX and SMAX load strongly on the short-term reversal factor REV. This reversal loading is intuitive since LMAX and SMAX go long stocks with low returns on their best days. IVOL has little loading on REV (so excluding REV from the right-hand side hardly changes the results; not shown).

Panel B of Table VII considers the three idiosyncratic factors in the global sample. In the global sample, the idiosyncratic risk factors have positive and significant three-factor alphas, but their alphas become insignificant once controlling for RMW, CMA, and REV.

In summary, the idiosyncratic risk factors LMAX, SMAX, and IVOL produce positive alphas in the U.S., but their alphas are weak outside the U.S. In addition, our new scaled factor SMAX appears more robust, especially in the U.S.

5. Testing the Underlying Economic Drivers

5.1. Economic Drivers based on Leverage Constraints and Behavioral Lottery Demand

Having decomposed the low-risk effect into a systematic and an idiosyncratic part, we next analyze the economic drivers of these two parts of the low-risk effect. To test the theory of leverage constraints, we include a measure of margin debt. Similarly, to test the behavioral theories, we consider measures of investor sentiment, casino profits, and lottery ticket sales. For each of these, we consider both the ex ante value and the contemporaneous change. Further, we control for the five Fama-French factors and short-term reversal factor such that we effectively predicts each factors alpha in excess of these factors, i.e., the parts of the return more unique to each factor.

The data sources of the economic variables are discussed in Section 2, but a brief comment on the measure of leverage constraints is in order. We construct a new measure of leverage constraints based on the amount of margin debt (MD) held against NYSE stocks as a fraction of the total market equity of NYSE stocks. When margin debt is low, we interpret this as tight leverage constraints, that is, we implicitly assume that the variation in the amount of margin debt is primarily driven by changes in the supply of leverage. This is a simplification, but, consistent with the idea that margin debt is high during times of favorable funding liquidity, margin debt is negatively correlated with the TED spread, noise in the term structure of U.S. government bonds as defined by Hu, Pan, and Wang (2013), and positively correlated with the leverage applied by financial intermediaries as seen Table A7 in the appendix. These signs of the correlations are the same whether all variables are measured in levels or changes as seen in Table A7.

Panel A of Table VIII tests the extent to which the different low-risk factors are predicted by margin debt and sentiment. As seen in the first four columns, both BAC and BAB have higher future return when ex ante margin debt is low, i.e.., when leverage constraints are high. Contemporaneous increases in margin debt are associated with positive returns to BAB and BAC, consistent with the theory that investors shifting their portfolios towards low-risk stocks when leverage constraints decrease. This contemporaneous effect is statistically significant. In other words, since prices should go in the opposite direction of expected returns, both of these findings are consistent with the theory of leverage constraints. Investor sentiment does not seem to have an influence on the return to BAB and BAC consistent with the idea that these factors capture leverage constraints rather than sentiment.

We next consider the determinants of the idiosyncratic risk factors, also reported in Panel A of Table VIII. We see that LMAX, IVOL and SMAX all have higher return when ex ante investor sentiment is high, consistent with the factors being driven, at least partly, by behavioral demand. The effect is statistically significant for IVOL and LMAX. The effect of the contemporaneous change in sentiment is insignificant for IVOL and LMAX while it appears to go in the wrong direction for SMAX. Finally, neither of the idiosyncratic factors LMAX, SMAX, and IVOL appear related to margin debt, which is consistent with leverage constraints influencing the price of systematic risk, but not the price of idiosyncratic risk.

In Panel B we test if the predictive power of sentiment comes directly from lottery demand. We find no reliable and significant predictive relation between casino profits and subsequent returns to the idiosyncratic low-risk factors. However, we do find that an increase in casino profits is associated with lower contemporaneous returns to the idiosyncratic low-risk factors, consistent with lottery demand partly driving the idiosyncratic part of the low-risk effect.

That said, we find no statistically significant effect of lottery tickets on the idiosyncratic low-risk factors. We note that the idiosyncratic low-risk factors are not very profitable in the first place in UK, which is the sample for our lottery ticket regressions.

To further address the hypothesis that BAB and BAC might be driven by demand for lottery, we also test if the lottery measures predict these factors. We find no evidence for this hypothesis. Neither BAB nor BAC load on either of the two lottery measures. This result is again consistent with the notion that lottery demand might influence the idiosyncratic low-risk factors, but not the systematic low-risk factors.

In summary, the evidence is consistent with leverage constraints causing the BAB and BAC factor returns while the evidence is mixed and weaker that lottery demand drives the idiosyncratic risk factors. We next test four alternative theories that have been proposed as explanations of the low-risk effect.

5.2. Mispricing and Arbitrage Risk

Liu, Stambaugh, and Yuan (2017) propose that stocks with high idiosyncratic risk have higher average mispricings since they are riskier to arbitrage (a form of limited of arbitrage). Further, the authors argue that the interaction of mispricing and idiosyncratic risk can help explain the low risk effect.

In one interesting test, Liu, Stambaugh, and Yuan (2017) double sort stocks on beta and mispricing (using the mispricing measure of Stambaugh, Yu, and Yuan (2015)). They find that, when keeping mispricing constant, the relationship between beta and 3-factor alpha only exist among overpriced stocks (echoing a related finding in Stambaugh, Yu, and Yuan (2015)).

There are several reasons that our analysis differs from that of Liu, Stambaugh, and Yuan (2017). First, the theory of leverage constraints predicts that high-beta stocks endogenously become over-priced (relative to the standard CAPM) so the theory does not make clear predictions for the alpha-beta relation when controlling for over-pricing, especially when one considers the 3-factor alpha rather than 1-factor alpha (i.e., controlling for over-pricing could "throw the baby out with the bathwater"). Second, their finding related to idiosyncratic volatility could confound the alpha-beta relation to the extent that there are multiple drivers of the low-risk effect. Third, they use a different measure of beta than the one that we use here. Fourth, they use a shorter sample (since they need the mispricing data). We discuss the first three effects (regarding the fourth issue, we must also focus on the shorter sample period when controlling for mispricing).

To get a cleaner test of the alpha-beta relation when controlling for overpricing, we sort stocks first by mispricing and then by our measure of correlation. By sorting on correlation instead of beta, we pick up the effect of systematic risk without also picking up the effect of idiosyncratic volatility. Panel C in Table VIII reports the results. Consistent with the theory of leverage constraints, higher correlation leads to lower alpha irrespective of the degree of over- or underpricing (looking across each row). Indeed, in all five mispricing quintiles, higher correlation leads to a lower alpha. The size of the alpha is also similar across mispricing quintiles. This provides further evidence of the theory of leverage constraints. At the same time, a higher mispricing is associated with a lower alpha for each level of correlation (looking across the columns), consistent with the idea that mispricing plays a separate role from leverage constraints.

In a different test, Liu, Stambaugh, and Yuan (2017) find that the low-risk effect disappears if one deletes stocks that are among the 20% most overpriced and simultaneous among the 25% highest IVOL. However, this finding arises because of their specific measures of alpha and beta and their sample, while the low-risk effect measured our way is robust to deleting these stocks. To see this, the appendix reports the magnitude of low-risk effect using their measures (Table A5) and using our measures (Table A6). Even using their measure of beta, deleting overpriced/risky stocks actually has little effect on the slope of the security market line (the relation between excess returns and beta) and it therefore does not influence the low-risk effect when measured using CAPM alpha. The low-risk effect does, however, become insignificant if one considers three-factor alpha because the return to low-risk portfolios is partly explained by HML – but as explained in section 3.3, the leverage constraints theory predicts only an effect of beta on CAPM alpha, not necessarily three-factor alpha. In addition, if we use our measure of beta (Table A6), we obtain a larger beta spread in beta-sorted portfolios and the low-risk effect remains significant even after deleting overpriced/risky stocks and controlling for the three-factor model.

In summary, the evidence based on the double sort supports both the theory of leverage constraints and, simultaneously, the idea that stocks can be mispriced due to other effects consistent with Stambaugh, Yu, and Yuan (2015) and Liu, Stambaugh, and Yuan (2017). The evidence based on deleting certain stocks provides further evidence on the robustness of the low-risk effect, although it also shows that there does exist certain sub-samples and certain measures of beta and alpha where the effect is weaker.

5.3. Alternative Economic Drivers

Money Illusion. To test the Modigliani-Cohn hypothesis of Money Illusion as proposed in this connection by Cohen, Polk, and Vuelteenaho (2005), we include inflation in Table VIII, Panel A. The sign of inflation is wrong relative to the Modigliani-Cohn hypothesis of money illusion so it seems unlikely that money illusion drives the low-risk effect.

Skewness and Co-Skewness. It is well known that the CAPM is based on specific assumptions, in particular that the representative investor has quadratic utility, implying that required returns only depend on the covariance (or beta) with the market return. However, with other utility functions, skew and other higher order moments also matter. For example, a representative investor with constant relative risk aversion (CRRA) is averse towards skew risk because this utility functions puts additional emphasis on the worst states of the market (Kraus and Litzenberger, 1976). Schneider, Wagner, and Zechner (2016) show that low-beta stocks have higher skew risk, in the sense that they do worse than their beta suggests in the worst realizations of the market, and argue that the high alpha of low-beta stocks may be compensation for such skew risk.

To address this issue, we first simply consider how beta-sorted portfolios perform in different market environments. Figure A1 plots the realized return to low- and high-beta portfolios as a function of the realized market return. Clearly, low-beta stocks have much higher returns than high-beta stocks when the market is down, especially when the market is way down. Hence, this theory has no chance to explain a flat security market line because low-beta stocks are certainly safer than high-beta stocks with respect to any stochastic discount factor that is monotonic in the market return (as implied by a representative agents with any standard utility function of the market return). More broadly, given that low-beta stocks have almost as high average returns as high-beta stocks, it is difficult to see why skew-averse investors would not prefer the low-beta stocks. Indeed, if we lever the low-beta portfolio 3.07 times such that it has the same return as high-beta portfolio during the months with the worst market returns, then the leveraged low-beta portfolio has an average excess return of 21% percent per year whereas the high-beta portfolio has an average return of only 6.8%. That is, the low-beta portfolio offers a much higher average return when leverage to the same skew risk.

Further, Figure A1 shows that both low-beta and high-beta average portfolio returns are close to linear in the market return. However, we can detect a small non-linearity in the most extreme cases. In particular, in the worst market outcomes, low-beta stocks perform slightly worse than implied by their beta while the reverse is true for high-beta stocks. This finding is consistent with the loading on the squared market return documented by Schneider, Wagner, and Zechner (2016). Therefore, risk skew averse agents would require a lower return spread between low-beta and high-beta stocks than what is implied by the CAPM, but how large is this effect?

Figure A2 in the appendix plots the required return to ten beta-sorted portfolios as implied by three different asset pricing models:[14] the CAPM, a CRRA investor with risk aversion of 3, and a CRRA investor with risk aversion of 10. We see that the lines are close together, meaning that skew risk has a relatively small effect on required returns. Further, all three lines are far from the realized returns illustrated with green dots, meaning that neither can explain the low-risk effect. Nevertheless, a CRRA investor would require slightly higher return on low-beta stocks than a CAPM investor because of skew risk. For example, with the highest risk aversion of 10, such an investor requires 0.56 times the market return in order to buy the low-beta

[14] The stochastic discount factor (SDF) of a CRRA investor with risk aversion of γ is proportional to $(1+r_t^m)^{-\gamma}$ so the required return of any security i is proportional to the covariance with the SDF, $-\mathrm{cov}[\, r_t^i \,, (1+r_t^m)^{-\gamma}\,]$.

portfolio, whereas the CAPM investor requires 0.51 times the market return. However, the CRRA investor still requires substantially less than the realized return on low-beta stocks.

In summary, either way that we look at the data, we that skew risk of this form is too small to explain the low-risk effect.

Time-Varying Betas. Finally, Cederburg and O'Doherty (2016) find that the low-risk effect is explained by time-varying conditional betas. This may seem like a puzzling statement given that the BAB factor is hedged ex ante to have a conditional beta of zero. A constant beta of zero does not vary! There are two reasons that time-varying betas might matter anyway: (1) the ex ante hedge used to construct BAB could be sufficiently imperfect; (2) Cederburg and O'Doherty (2016) actually ignore the BAB factor and construct their own low-beta factor, which is not constructed to be beta neutral.

Let us start with the second reason. The low-minus-high beta portfolio of Cederburg and O'Doherty (2016) simply has a low CAPM alpha even before adjusting for time-varying betas (due to their use of quarterly returns, not using NYSE breakpoints, measure of beta, and factor construction). Hence, they start with a low-beta factor with a low alpha and do not hedge market exposure ex ante (as BAB), concluding that they fail to reject that the low-beta effect is different from zero. However, failing to reject a test may simply mean that the test has low power, but such a finding does not imply that the low-risk effect is zero when stronger tests succeed to reject. For example, Liu, Stambaugh, and Yuan (2017) vary the methodology of Cederburg and O'Doherty slightly, and they find that controlling for conditional betas cannot explain the low-risk effect (Table A.2). In fact, in Liu, Stambaugh, and Yuan's regressions, the low-risk effect becomes slightly larger after controlling for conditional betas. More broadly, we note that the use of instruments by Cederburg and O'Doherty (2016) to control for variation in betas is subject to the Hansen and Richard (1987) critique, namely that we cannot know if we have used the right instruments.

If time-varying betas was a concern, it would be natural to use the BAB factor since its ex ante beta is hedged to zero. Even if the true ex ante beta is different from zero (due to measurement error), it is unlikely that all of its 0.73 monthly CAPM alpha can be explained by time varying betas. For instance, as shown in Table 1 of Lewellen and Nagel (2006), conditional market timing explains at most 0.25 percent monthly alpha if the monthly standard deviation of betas is 0.5, which would be a remarkable monthly variation for a strategy that is hedged to have a constant conditional beta of zero. Further, Gormsen and Jensen (2017) explicitly test the effect of time-varying betas of the BAB factor using a non-instrumental approach, finding that time-variation in betas can explain only around 20% of BAB's CAPM alpha.

6. Horserace

The analysis so far suggests that the low-risk effect is driven by both systematic and idiosyncratic risk due to, respectively, leverage constraints and lottery demand. Our analysis suggests that the competing explanations share an element related to volatility, but also have separate elements related to, respectively, correlation and the shape of the return distribution. To further judge whether both explanations have separate power and their relative importance in the low-risk effect, we now run a "horserace."

6.1. Horserace based on published factors

We first consider a horserace between the various factors constructed as in the papers where they were first considered (as we have also done in the previous analysis). Table IX shows the results of regressing each systematic/idiosyncratic risk factor on a competing factor (BAB or LMAX) as well as several controls, namely the five Fama-French factors and the reversal factor REV.

Panel A of Table IX reports our findings for US factors. The BAB factor in the U.S. has a positive and significant alpha (*t*-statistic of 3.0) when controlling for LMAX, the five Fama-French factors, and REV. Further, we see that BAC has an even more significant alpha when controlling for these factors: BAC has an alpha of 0.6 percent per month with a *t*-statistic of 4.8. The higher alpha of BAC is likely due to the fact that it is constructed to be less correlated to other factors. Indeed, BAC has a much smaller factor loading on LMAX than BAB, although both are significantly positive. Collectively, these findings are evidence that the low-risk effect is not simply explained by a combination of idiosyncratic risk and the five Fama-French factors.

Finally, we see in Panel A of Table IX that BAV is not robust to controlling for LMAX, the five Fama-French factors, and REV. This finding is not surprising since BAV captures the part of BAB that is most closely connected to the idiosyncratic risk factors such as LMAX. When we have similar variables on the left-hand side and right-hand side, the intercept is naturally insignificant. Indeed, recall that BAV has significant excess returns, 1-factor, and 3-factor alpha, so its alpha only turns insignificant when we control for all other factors, which could simply reflect that the collection of right-hand-side variables already capture effects of leverage constraints (as discussed above).

We next turn our attention to the idiosyncratic factors in Table IX. We see that LMAX and IVOL have insignificant alphas in these regressions where we control for BAB, the five

Fama-French factors, and REV. Given our earlier results, this finding reflects that BAB drives the alpha of these factors to zero. However, SMAX has a positive and significant alpha. The fact that SMAX is the only idiosyncratic risk factor that retains its alpha may be because it is constructed to be more exclusively focused on idiosyncratic skewness, making it less correlated to BAB (and perhaps the other factors).

Panel B of Table IX shows the same factor regressions in the global sample. Again, we see that BAB and BAC have significant alphas, highlighting the importance of systematic risk in the global low-risk effect. None of the idiosyncratic factors has significant alpha in the global sample.

6.2. Turnover and alpha decay

So far, we have followed the literature and considered factors constructed as in the papers that first developed these factors, but these methodologies differ across factors. In particular, BAB (and, likewise, BAC and BAV) are rank-weighted while the others are based on the Fama-French methodology. Further, the factors have different turnover: LMAX, SMAX, and IVOL are based on monthly characteristics that change quickly, and thus have high turnover relative to BAB and the Fama-French factors that are more stable. We address both of these issues in order to make apples-to-apples comparisons.

We first consider turnover. Table X shows that LMAX and IVOL have much faster turnover than BAB, BAC, and BAV. Indeed, LMAX and IVOL have a monthly turnover of about 2 dollars. Said differently, an idiosyncratic volatility factor that goes long \$1 and shorts \$1 has an annual turnover of about 12×\$2=\$24. In contrast, the FF and BAB-type factors have about six times lower turnover (e.g., BAC has a monthly turnover of 0.35 dollars). This large difference in turnover is partly explained by the length of the time periods over which the characteristics are estimated: MAX and IVOL are both estimated over the previous month, whereas the characteristics used for the BAB-type factors are estimated over one to five years. Further, the characteristics of correlation and volatility may simply be more stable economic characteristics than variables such as MAX. The high turnover of the MAX and IVOL factors makes them more difficult to interpret, for instance because it may be more difficult for behavioral investors to keep track of such transient properties. Further, the high turnover means that these factors are more sensitive to microstructure issues, noise, and trading cost. To capture one element of these issues, we have included the factor REV, but constructing more stable characteristics is a much more direct way to address the turnover issue.

We introduce a new one-year MAX characteristic that calculates max returns over the last year rather than the last month and a corresponding factor that we denote LMAX(1Y). The characteristic is simply the average return on the 20 highest return days. Similarly, we construct the factor SMAX(1Y) based on volatility-scaled MAX returns over the 1-year look-back period.

As can be seen in Table X, the idiosyncratic risk factors with 1-year lookback period, namely LMAX(1Y) and SMAX(1Y), have substantially lower turnover than their monthly counterparts. Nevertheless, these factors still have higher turnover than the BAB and Fama-French factors.

Table XI shows the return to LMAX(1Y) and SMAX(1Y). We see that LMAX(1Y) has significant three-factor alpha, but the alpha is driven out when controlling for RMW, CMA, and REV. For SMAX(1Y), the situation is worse. The factor has insignificant three-factor alpha, and significantly negative alpha once controlling for RMW, CMA, and REV. These results suggest that the factors get much of their alphas from the high turnover.

Another way to illustrate the importance of turnover is to consider how quickly the alpha decays after portfolio formation. To illustrate the alpha decay of the various factors, Figure 1 plots the cumulative alpha in event time, relative to the portfolio formation period. Panel A of Figure 1 plots the 3-factor alphas while Panel B plots 5-factor alphas.

As can be seen in Panel A, the cumulative alphas of the BAB and BAC factors grow continually over the year after the portfolio formation period. To understand what happens, note that low-beta stocks typically remain low-beta stocks over the following 12 months and, therefore, they continue to earn positive alphas. Likewise, the cumulative 3-factor alphas of LMAX and LMAX-1-year gradually rise over the next 12 months, although these curves flatten out. The cumulative alpha of SMAX is striking: It flattens out after 1 month, meaning that all of the three-factor alpha associated with the monthly SMAX characteristic is earned in the first month – holding SMAX for longer does not give any additional alpha.

Panel B of figure 5 shows cumulative five-factor alpha in event time, that is, the same as Panel A except that we now also control for the quality factors RMW and CMA. For BAB and BAC, the results are similar to those of Panel A, reflecting that the BAB and BAC factors continue to earn alpha, whether the 3-factor or 5-factor model is used, over the 12 months following portfolio formation. However, now all of the idiosyncratic risk factors have flat cumulative alpha curves, looking similar to the flat alpha curve for SMAX in Panel A. In other words, as for SMAX, LMAX and even the version with 1-year-lookback now only earn alpha in the month following portfolio formation and holding it for longer hardly contributes with additional alpha. This difference in the persistence of three-factor and five-factor alpha for LMAX is due to the loading of LMAX on the quality factors (profitability and investment). Indeed, it seems that LMAX picks up a slow-moving return pattern captured by RMW and

CMA, but, once we control for RMW and CMA, the effect disappears and only a transient return component remains.

6.3. All factors constructed based on Fama-French methodology

We next run a horserace where all factors are constructed based on the Fama-French methodology. In particular, all factors are constructed by double sorting on size and the characteristic in question, creating value-weighted portfolios, and going long a small and a big one and shorting a small and a big one (as described in Section 2). For BAC and BAV, we continue to create volatility (correlation) neutral editions of the factors. That is, within each volatility (correlation) quintile, we create a Fama-French-type factor based on stocks' correlation (volatility) characteristic, and then finally take an equal-weighted average of these five factors.

The results are reported in Table XII. As is seen in the table, BAB, BAC, and BAV have positive and significant alphas when controlling for the five Fama-French factors and REV. These results thus reject the claim by Fama and French (2016) that the low-risk effect is explained by the five-factor model. The alpha for BAB and BAC, however, become insignificant once also controlling for LMAX, but the alpha of BAV is robust to controlling for LMAX. Looking at idiosyncratic risk factors, SMAX is the only factor with significant alpha. In the global sample, only BAV produce significant alpha.

6.4. All factors constructed based on rank-weighting-BAB methodology

We next run a horserace where all factors are rank-weighted. Since some of the Fama and French characteristics, such as book-to-price, are highly correlated with size, we make all the rank-weighted factors size neutral. For each factor we, similarly to Fama and French (1993), first assign stocks into two groups based on the median NYSE size and then create a rank-weighted factor within each size group. Each factor is then the average return to the two rank-weighted factors. That is, for HML for instance, the return is given by

$$HML_{t+1}^{Rank} = 0.5HML_{t+1}^{Rank,small} + 0.5HML_{t+1}^{Rank,large}$$

where the rank-weighted returns are calculated using the method of Frazzini and Pedersen (2014) such that the portfolios are hedged ex-ante to have a beta of zero. We also construct new editions of BAB, BAC, and BAV using the above method.

Table XIII shows the results for the rank-weighted portfolios. As we already knew, BAB and BAC work well with rank weights and the factors thus have large Sharpe ratios. What is new in Table XIII, however, is that their alphas are robust to using rank-weighted factors on the right hand side. Indeed, the alpha for BAB is essentially the same as when we use the traditional Fama-French factors on the right hand side in Table IX. The alpha for BAC is a little lower than in Table IX but it remains highly significant.

The alphas for the idiosyncratic risk factors are generally not robust to using rank weights. Only the six-factor alpha of SMAX is statistically significant, but this alpha becomes insignificant once controlling for BAB. It is worth noting that using rank weights actually also "works" for the idiosyncratic in the sense that these rank-weighted factors have larger Sharpe ratios than their Fama-French-type counterparts. The reason that the rank-weighted idiosyncratic risk factors nevertheless have negative alphas is that the rank-weighted right-hand-side factors are even more effective in explaining them.

7. Conclusion

The low-risk effect has profound implications for investors, firms, and capital markets. Can investors benefit from low-risk stocks if they learn to overcome their biases? Or, are their hands tied by leverage constraints? These questions are not just academic as most assets are controlled by institutional investors where leverage constraints are in principle directly observable – and changeable! – e.g., for many pension funds and mutual funds. Likewise, if professional asset managers really suffer from sentiment-based lottery demand such that they change their preference for stocks based on the returns over the past month then perhaps this bias can be alleviated by education.

Further, the low-risk effect impacts firms' cost of capital and, hence, possibly their investment decisions and other corporate behavior. Should firms try to undertake lottery-like real investments to lower their cost of capital? Or should they simply add some debt to their balance sheet (relative to what they would do in the absence of the low-risk effect)?

We contribute to the literature that seeks to address these questions in four ways. First, we present new evidence consistent specifically with the theory of leverage constraints by showing that low-correlation stocks have high risk-adjusted returns that cannot be explained by other low-risk factors. Both in the U.S. and internationally, our BAC factor produces statistically significant six-factor alpha that is close to orthogonal to other low-risk factors.

Second, we present a new factor SMAX that captures the returns to betting against stocks with lottery-like return distributions. SMAX has positive risk-adjusted returns in the US, but not globally – as is the case for other idiosyncratic risk factors.

Third, we show that the tightness of margin constraints predicts the return to systematic low-risk factors, but not that of the idiosyncratic low-risk factors. On the other hand, investor sentiment (but not lottery ticket sales or casino profits) predicts the return to some of the idiosyncratic low-risk factors, but not that of the systematic factors BAB and BAC.

Fourth, in horseraces between the low-risk factors, we find that systematic low-risk factors tend to outperform idiosyncratic low-risk factors. The outperformance of the systematic low-risk factors becomes even more pronounced once all the low-risk factors are put on a level playing field in terms of turnover since the idiosyncratic risk factors derive much of their alphas from a short-term effect.

In conclusion, our results suggest that both leverage constraints and lottery demand play a role for the low-risk effect. The results are stronger for leverage constraints, especially outside the US, consistent with the underlying equilibrium theory and the fact that these constraints are observable for many investors.

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Table I
Summary Statistics

This table shows summary statistics as of June of each year. The sample includes all U.S. common stocks (CRSP "shrcd" equal to 10 or 11) and all global stocks ("tcpi" equal to 0) in the merged CRSP/Xpressfeed global databases.

Country	Total number of stocks	Average number of stocks	Firm size (Billion-USD)	Weight in global portfolio	Start Year	End Year
Australia	3,286	1,027	0.61	0.018	1985	2015
Austria	217	84	0.82	0.002	1986	2015
Belgium	445	147	1.90	0.009	1986	2015
Canada	2,106	576	1.20	0.022	1982	2015
Switzerland	596	226	3.72	0.024	1986	2015
Germany	2,414	850	3.09	0.071	1986	2015
Denmark	411	156	1.01	0.004	1986	2015
Spain	415	147	3.65	0.015	1986	2015
Finland	307	117	1.32	0.004	1986	2015
France	1,932	641	2.35	0.044	1986	2015
United Kingdom	6,371	2,013	1.63	0.102	1986	2015
Greece	425	186	0.40	0.002	1988	2015
Hong Kong	2,510	816	1.50	0.030	1986	2015
Ireland	157	53	1.52	0.002	1986	2015
Israel	724	282	0.39	0.003	1994	2015
Italy	686	245	2.34	0.018	1986	2015
Japan	5,309	3,053	1.21	0.188	1986	2015
Netherlands	423	173	3.58	0.020	1986	2015
Norway	719	185	0.85	0.004	1986	2015
New Zealand	349	112	1.04	0.003	1986	2015
Portugal	157	63	1.56	0.002	1988	2015
Singapore	1,259	474	0.71	0.011	1986	2015
Sweden	1,201	309	1.44	0.012	1986	2015
United States	24,218	3,328	1.21	0.389	1926	2015

Table II
Correlation vs. Volatility: Beta and Risk-Adjusted Returns

This table shows properties of 25 portfolios of U.S. stocks from 1926 to 2015. At the beginning of each calendar month, stocks are sorted first on ex ante volatility and then conditionally on ex ante correlation. Specifically, the stocks are assigned to one of five volatility quintiles based on NYSE breakpoints. Within each quintile, stocks are assigned to one of five correlation quintile portfolios based on NYSE breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. The long-short portfolios are self-financing portfolios that are long $1 in the portfolio with highest correlation (volatility) within each volatility (correlation) quintile and short $1 in the portfolio with lowest correlation (volatility) within the same volatility (correlation) quintiles. Panel A reports CAPM betas and Panel B reports CAPM alphas, i.e., respectively the slope and intercept in a regression of monthly excess return on excess returns to the CRSP value-weighted market portfolio (MKT). Panel B reports three-factor alphas, i.e., the intercept in a regression of monthly excess return on MKT, size (SMB), and value (HML) factors of Fama and French (1993). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates and 5% statistical significance is indicated in bold.

US 1930-2015

Panel A: CAPM beta

Sort on volatility	Conditional sort on correlation: P1 (low)	P2	P3	P4	P5 (high)	LS
P1 (low)	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.4**
						(24.9)
P2	**0.7**	**0.9**	**1.0**	**1.1**	**1.2**	**0.5**
						(26.2)
P3	**0.7**	**1.0**	**1.2**	**1.3**	**1.4**	**0.7**
						(27.1)
P4	**0.8**	**1.0**	**1.2**	**1.3**	**1.6**	**0.8**
						(24.3)
P5 (high)	**0.8**	**1.0**	**1.1**	**1.3**	**1.6**	**0.8**
						(15.3)
LS	**0.4**	**0.5**	**0.5**	**0.5**	**0.7**	
	(8.3)	(12.6)	(15.3)	(17.0)	(21.1)	

US 1930-2015

Panel B: CAPM alpha

Sort on volatility	Conditional sort on correlation: P1 (low)	P2	P3	P4	P5 (high)	LS
P1 (low)	**0.4**	**0.3**	**0.2**	**0.1**	**0.1**	**-0.3**
	(5.6)	(3.9)	(3.2)	(2.1)	(2.3)	(-3.6)
P2	**0.3**	**0.2**	0.1	0.1	-0.1	**-0.3**
	(3.3)	(2.1)	(1.6)	(0.7)	(-0.7)	(-3.0)
P3	**0.4**	**0.3**	0.1	0.0	**-0.2**	**-0.6**
	(4.1)	(2.8)	(0.6)	(-0.2)	(-2.3)	(-4.4)
P4	**0.4**	**0.3**	0.0	-0.1	**-0.3**	**-0.7**
	(3.3)	(2.3)	(0.3)	(-1.0)	(-2.2)	(-4.2)
P5 (high)	0.3	0.1	0.1	-0.3	**-0.5**	**-0.8**
	(1.4)	(0.2)	(0.4)	(-1.7)	(-2.7)	(-3.3)
LS	-0.1	-0.2	-0.2	**-0.4**	**-0.6**	
	(-0.5)	(-1.0)	(-0.8)	(-2.2)	(-3.0)	

Table II
Correlation vs. Volatility: Beta and Risk-Adjusted Returns (Continued)

US 1930-2015

Panel C: Three-factor al

		Conditional sort on correlation					
		P1 (low)	P2	P3	P4	P5 (high)	LS
Sort on volatility	P1 (low)	**0.4**	**0.2**	**0.2**	0.1	**0.1**	**-0.3**
		(5.2)	(3.3)	(2.6)	(1.8)	(2.9)	(-3.3)
	P2	**0.2**	0.1	0.1	0.0	-0.1	**-0.3**
		(2.6)	(1.1)	(0.8)	(-0.6)	(-1.6)	(-3.0)
	P3	**0.3**	0.1	-0.1	**-0.2**	**-0.4**	**-0.6**
		(3.4)	(1.5)	(-1.4)	(-2.4)	(-4.2)	(-4.9)
	P4	**0.3**	0.1	-0.2	**-0.3**	**-0.5**	**-0.8**
		(2.4)	(1.1)	(-1.5)	(-2.9)	(-4.4)	(-4.5)
	P5 (high)	0.1	-0.2	-0.1	**-0.5**	**-0.7**	**-0.8**
		(0.4)	(-0.9)	(-1.1)	(-3.9)	(-4.5)	(-3.2)
	LS	-0.3	**-0.4**	**-0.3**	**-0.6**	**-0.9**	
		(-1.4)	(-2.1)	(-2.0)	(-4.0)	(-4.9)	

Table III
Betting Against Beta as Betting Against Correlation and Volatility

This table shows the results of regressions of the monthly return to betting against beta (BAB) on the monthly return to betting against correlation (BAC) and betting against volatility (BAV). Panel A reports results in the U.S. sample and panel B reports the results in the global sample. *t*-statistics are shown in parenthesis below the coefficient estimates and 5% statistical significance is indicated in bold.

Panel A: Long U.S. Sample (1930-2015)		Panel B: Global sample (1990-2015)	
	BAB		BAB
Intercept	0.00	Intercept	0.00
	(-1.56)		(-0.02)
BAC	**0.71**	BAC	**0.84**
	(63.00)		(66.77)
BAV	**0.51**	BAV	**0.49**
	(60.33)		(58.52)
R2	0.85	R2	0.96
Num	1020		306

Table IV
Betting Against Correlation

This table shows returns to the betting against correlation (BAC) factor in each volatility quintile, along with the equal-weighted average of these factors, which constitute our overall BAC factor. Panel A reports the BAC performance in the U.S. sample and panel B reports the performance in the global sample. At the beginning of each month stocks are ranked in ascending order based on the estimated of volatility at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are assigned to one of two portfolios: low correlation and high correlation. In these portfolios, stocks are rank-weighted by correlation (lower correlation stocks have larger weights in the low-correlation portfolios and larger correlation stocks have larger weights in the high-correlation portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. Within each volatility quintile, a self-financing BAC portfolio is made that is long the low-correlation portfolio and short the high-correlation portfolio. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's total (lagged) market capitalization. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML, RMW, and CMA factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. '\$ long' and '\$ short' measures how many dollars the betting against correlation portfolio is long and short. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1963-2015)					
Volatility quintile	1	2	3	4	5	BAC
Excess return	**0.55**	**0.86**	**0.92**	**1.03**	**1.48**	**0.97**
	(4.32)	(6.52)	(6.31)	(5.88)	(5.78)	(6.74)
Alpha	**0.39**	**0.63**	**0.57**	**0.68**	**1.25**	**0.70**
	(3.56)	(5.50)	(4.26)	(4.08)	(4.96)	(5.45)
MKT	**-0.14**	-0.05	0.05	**0.09**	**0.13**	0.02
	(-5.1)	(-1.9)	(1.5)	(2.2)	(2.14)	(0.5)
SMB	**0.62**	**0.61**	**0.58**	**0.58**	**0.61**	**0.60**
	(16.6)	(15.7)	(12.7)	(10.1)	(7.1)	(13.6)
HML	**0.12**	**0.17**	**0.26**	**0.31**	0.23	**0.22**
	(2.3)	(3.2)	(4.0)	(3.9)	(1.9)	(3.5)
RMW	0.02	0.05	**0.17**	0.16	**-0.28**	0.02
	(0.4)	(0.9)	(2.5)	(1.9)	(-2.2)	(0.3)
CMA	0.08	0.08	0.18	0.04	0.01	0.08
	(1.0)	(0.9)	(1.9)	(0.4)	(0.0)	(0.8)
SR	0.60	0.90	0.87	0.81	0.80	0.93
IR	0.52	0.80	0.62	0.59	0.72	0.79
R2	0.34	0.31	0.25	0.18	0.13	0.27
# obs	630	630	630	630	630	630

Table IV
Betting Against Correlation (continued)

	Panel B: Global Sample (1990-2015)					
Volatility quintile	1	2	3	4	5	BAC
Excess return	**0.27**	**0.64**	**0.64**	**0.70**	**1.15**	**0.68**
	(2.08)	(4.57)	(3.98)	(3.95)	(4.55)	(4.48)
Alpha	0.11	**0.41**	0.27	0.24	**0.81**	**0.37**
	(0.99)	(3.19)	(1.84)	(1.48)	(3.39)	(2.77)
MKT	0.01	**0.07**	**0.15**	**0.18**	**0.21**	**0.12**
	(0.4)	(2.0)	(3.7)	(4.1)	(3.27)	(3.5)
SMB	**0.65**	**0.71**	**0.75**	**0.85**	**1.11**	**0.81**
	(11.9)	(11.5)	(10.6)	(10.8)	(9.6)	(12.6)
HML	0.10	0.14	**0.26**	**0.23**	0.05	0.16
	(1.4)	(1.9)	(2.9)	(2.4)	(0.4)	(1.9)
RMW	**0.18**	**0.31**	**0.49**	**0.71**	**0.41**	**0.42**
	(2.2)	(3.3)	(4.6)	(6.0)	(2.3)	(4.3)
CMA	0.10	0.09	0.08	0.11	0.15	0.10
	(1.2)	(0.9)	(0.7)	(0.8)	(0.8)	(1.0)
SR	0.41	0.90	0.79	0.78	0.90	0.89
IR	0.21	0.69	0.40	0.32	0.73	0.60
R2	0.33	0.31	0.29	0.30	0.23	0.35
# obs	306	306	306	306	306	306

Table V
SMAX vs. Volatility: Risk-Adjusted Returns

This table shows the risk adjusted returns to 25 portfolios sorted first on volatility and then conditionally on SMAX in the U.S. from 1926 to 2015. At the beginning of each calendar month, stocks are ranked in ascending order based on the estimate of volatility at the end of the previous month. The ranked stocks are assigned to one of five quintiles based on NYSE breakpoints. Within each quintile, stocks are ranked in ascending order based on the estimate of SMAX at the end of the previous month and assigned to one of five quintile portfolios based on NYSE breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. The long-short portfolios are self-financing portfolios that are long $1 in the portfolio with highest SMAX (volatility) within each volatility (SMAX) quintile and short $1 in the portfolio with lowest SMAX (volatility) within the same volatility (SMAX) quintiles. SMAX is the average of the five highest daily returns for a stock over the previous month dividend by its volatility. Volatility is estimated as daily volatility over the previous month. Panel A reports CAPM alphas, Panel B reports three-factor alphas (Mkt, SMB, HML), and Panel C reports five-factor alpha (MKT, SMB, HML, RMW, CMA). Alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates and 5% statistical significance is indicated in bold.

US 1930-2015

Panel A: CAPM alpha

		Conditional sort on SMAX					
		P1 (low)	P2	P3	P4	P5 (high)	LS
Sort on volatility	P1 (low)	**0.3**	**0.2**	0.1	**0.1**	0.1	**-0.3**
		(5.4)	(3.2)	(1.4)	(2.0)	(1.1)	(-3.4)
	P2	**0.3**	**0.2**	0.1	0.0	**-0.2**	**-0.5**
		(3.8)	(2.5)	(1.6)	(0.1)	(-2.7)	(-5.0)
	P3	**0.3**	0.2	-0.1	-0.1	**-0.4**	**-0.7**
		(3.6)	(1.7)	(-1.3)	(-1.3)	(-3.8)	(-5.5)
	P4	**0.4**	0.1	-0.1	**-0.3**	**-0.5**	**-0.9**
		(3.5)	(1.1)	(-0.9)	(-2.1)	(-3.7)	(-6.2)
	P5 (high)	**0.4**	0.0	-0.2	**-0.5**	**-0.8**	**-1.2**
		(2.0)	(-0.0)	(-0.8)	(-2.6)	(-3.8)	(-5.5)
	LS	0.0	-0.2	-0.2	**-0.7**	**-0.9**	
		(0.2)	(-1.0)	(-1.0)	(-2.8)	(-3.7)	

US 1930-2015

Panel B: Three-factor alpha

		Conditional sort on SMAX					
		P1 (low)	P2	P3	P4	P5 (high)	LS
Sort on volatility	P1 (low)	**0.3**	**0.2**	0.1	0.1	0.1	**-0.3**
		(5.4)	(3.3)	(1.1)	(1.9)	(1.0)	(-3.4)
	P2	**0.2**	0.1	0.1	-0.1	**-0.3**	**-0.5**
		(3.1)	(1.8)	(0.9)	(-0.9)	(-3.9)	(-5.1)
	P3	**0.2**	0.0	**-0.3**	**-0.2**	**-0.5**	**-0.7**
		(2.8)	(0.3)	(-3.1)	(-2.9)	(-5.4)	(-5.7)
	P4	**0.3**	0.0	**-0.2**	**-0.4**	**-0.6**	**-0.9**
		(3.0)	(-0.3)	(-2.4)	(-3.9)	(-5.6)	(-6.3)
	P5 (high)	**0.4**	-0.2	-0.3	**-0.8**	**-1.0**	**-1.3**
		(2.3)	(-0.9)	(-1.9)	(-4.3)	(-5.2)	(-6.2)
	LS	0.0	**-0.4**	**-0.4**	**-0.9**	**-1.0**	
		(0.3)	(-2.0)	(-2.0)	(-4.4)	(-5.1)	

Table VI
LMAX as SMAX and BAV

This table shows the results of regressions of the monthly return to the factor going long stocks with low maximum return over the past month (LMAX) on the monthly returns to the factor going long stocks with low maximum return scaled by volatility (SMAX) and the monthly return to the factor going long stocks with low total volatility (TV). Total volatility is total daily volatility measured over the previous month. *t*-statistics are shown in parenthesis below the coefficient estimates and 5% statistical significance is indicated in bold.

Panel A: Long U.S. Sample (1930-2015)		Panel B: Global sample (1990-2015)	
	LMAX		LMAX
Intercept	0.00	Intercept	0.00
	(1.33)		(1.24)
SMAX	**0.34**	SMAX	**0.23**
	(16.16)		(9.09)
TV	**0.75**	TV	**0.80**
	(83.92)		(81.26)
R2	0.90	R2	0.97
Num	1020	Num	306

Table VII
The Idiosyncratic Factors: LMAX, SMAX, and IVOL

This table shows regression results for monthly returns to the factor going long stocks with low maximum return over the past month (LMAX), the factor going long stocks with low maximum return scaled by volatility (SMAX), and the factor going long stocks with low idiosyncratic volatility (IVOL). Panel A reports the results from the U.S. sample and Panel B reports the results from the global sample. Total volatility is total daily volatility measured over the previous month. The intercept alpha is in monthly percent. The control variables are the monthly excess return to the market portfolio (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and short-term reversal (REV). *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. The Sharpe ratio (SR) and information ratio (IR) are annualized.

	Panel A: U.S. FMAX Sample (1963-2015)							
	SMAX	SMAX	SMAX	LMAX	LMAX	LMAX	IVOL	IVOL
Alpha	**0.44**	**0.38**	**0.25**	**0.58**	**0.31**	**0.24**	**0.53**	**0.22**
	(5.60)	(4.78)	(3.69)	(5.81)	(3.34)	(2.64)	(5.27)	(2.46)
MKT	**-0.04**	-0.02	**-0.09**	**-0.42**	**-0.35**	**-0.39**	**-0.44**	**-0.35**
	(-2.0)	(-1.2)	(-5.4)	(-17.8)	(-15.8)	(-17.40)	(-18.2)	(-16.2)
SMB	-0.02	0.01	-0.03	**-0.48**	**-0.35**	**-0.37**	**-0.65**	**-0.50**
	(-0.7)	(0.3)	(-1.1)	(-14.3)	(-11.2)	(-12.0)	(-19.7)	(-16.8)
HML	**0.08**	0.04	-0.03	**0.45**	**0.24**	**0.20**	**0.41**	**0.18**
	(2.8)	(1.1)	(-0.9)	(12.6)	(5.5)	(4.8)	(11.4)	(4.4)
RMW		**0.12**	**0.12**		**0.57**	**0.57**		**0.68**
		(3.0)	(3.6)		(12.3)	(12.7)		(15.5)
CMA		0.08	**0.16**		**0.46**	**0.50**		**0.49**
		(1.4)	(3.4)		(6.9)	(7.8)		(7.8)
REV			**0.36**			**0.19**		-0.01
			(16.9)			(6.6)		(-0.5)
SR	0.78	0.78	0.78	0.34	0.34	0.34	0.22	0.22
IR	0.79	0.70	0.54	0.82	0.49	0.39	0.74	0.36
R2	0.03	0.04	0.34	0.64	0.71	0.73	0.69	0.78
# obs	630	630	630	630	630	630	630	630

Table VII

The Idiosyncratic Factors: LMAX, SMAX, and IVOL (continued)

	Panel B: Global Sample (1990-2015)							
	SMAX	SMAX	SMAX	LMAX	LMAX	LMAX	IVOL	IVOL
Alpha	**0.19**	0.10	0.05	**0.45**	0.02	-0.01	**0.46**	-0.01
	(1.97)	(1.01)	(0.63)	(3.71)	(0.16)	(-0.12)	(3.76)	(-0.09)
MKT	**-0.07**	-0.03	**-0.10**	**-0.56**	**-0.35**	**-0.39**	**-0.51**	**-0.30**
	(-3.1)	(-1.1)	(-4.5)	(-20.2)	(-11.9)	(-13.60)	(-18.4)	(-10.3)
SMB	-0.02	0.02	0.04	**-0.49**	**-0.26**	**-0.25**	**-0.68**	**-0.43**
	(-0.5)	(0.5)	(1.0)	(-8.4)	(-5.0)	(-5.1)	(-11.6)	(-8.5)
HML	**0.18**	**0.14**	0.06	**0.57**	**0.18**	**0.14**	**0.56**	0.11
	(4.2)	(2.2)	(1.2)	(10.7)	(2.8)	(2.3)	(10.5)	(1.7)
RMW		**0.19**	**0.22**		**0.83**	**0.85**		**0.86**
		(2.5)	(3.9)		(10.4)	(11.2)		(11.2)
CMA		0.05	**0.14**		**0.61**	**0.66**		**0.72**
		(0.7)	(2.3)		(7.2)	(8.2)		(8.7)
REV			**0.39**			**0.21**		**0.07**
			(14.6)			(6.0)		(2.0)
SR	0.43	0.43	0.43	0.34	0.34	0.34	0.35	0.35
IR	0.40	0.22	0.14	0.75	0.03	-0.03	0.76	-0.02
R2	0.09	0.10	0.48	0.69	0.78	0.81	0.68	0.80
# obs	306	306	306	306	306	306	306	306

Table VIII
Economic Drivers of the Low-Risk Effect

This table reports results on the economic drivers of the low-risk effect. The dependent variables are the excess returns to betting against beta (BAB), betting against correlation (BAC), betting against volatility (BAV), the factor going long stocks with low maximum return over the past month (LMAX), the factor going long stocks with low maximum return scaled by volatility (SMAX), and the factor going long stocks with low idiosyncratic volatility (IVOL). The independent are MD, SENT, INF, Casino, and Lottery. MD is the amount of margin debt on NYSE firms held at dealer-brokers divided by the market capitalization of NYSE firms. SENT is the sentiment index of Baker and Wurgler (2006) multiplied by 100 for ease of interpretation. INF is the average change in the consumer price index over the last year. Casino is the profits in the casino industry in the previous quarter dividend by GDP. Lottery is the total sale of lottery tickets in UK over the previous month divided by GDP. We include as control variables the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML, RMW, and CMA factors of Fama and French (2015) and the short-term reversal factor from Ken French's data library. We use UK factors in all regressions where the Lottery measure is on the right-hand side. Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold.

Panel A: Margin Debt and Sentiment

	$BAB_{t;t+1}$	$BAB_{t;t+1}$	$BAC_{t;t+1}$	$BAC_{t;t+1}$	$LMAX_{t;t+1}$	$LMAX_{t;t+1}$	$SMAX_{t;t+1}$	$SMAX_{t;t+1}$	$IVOL_{t;t+1}$	$IVOL_{t;t+1}$
MD_t	-0,31	**-0,60**	-0,36	**-0,76**		0,18		-0,03		0,14
	(-1,69)	(-2,78)	(-1,87)	(-3,30)		(1,14)		(-0,22)		(0,91)
MD_{t+1}-MD_t	**6,18**	**5,74**	**10,45**	**9,30**		-2,03		0,88		-1,96
	(3,55)	(3,17)	(5,63)	(4,83)		(-1,51)		(0,86)		(-1,49)
$SENT_t$		0,13		-0,06	**0,21**	0,17	0,09	0,07	**0,24**	**0,24**
		(1,09)		(-0,46)	(2,35)	(1,85)	(1,35)	(1,03)	(2,79)	(2,69)
$SENT_{t+1}$-$SENT_t$		1,07		1,24	0,55	0,69	**1,03**	**1,03**	0,00	0,11
		(1,33)		(1,44)	(0,91)	(1,14)	(2,27)	(2,24)	(0,01)	(0,19)
INF_t		**-0,10**		**-0,16**		-0,03		-0,03		0,03
		(-2,03)		(-3,14)		(-0,75)		(-1,18)		(0,77)
INF_{t+1}-INF_t		-0,30		-0,19		**-0,65**		-0,17		-0,42
		(-1,00)		(-0,58)		(-2,90)		(-0,98)		(-1,89)
Controls										
Mkt	**0,16**	**0,16**	**0,12**	**0,11**	**-0,38**	**-0,41**	**-0,09**	**-0,08**	**-0,35**	**-0,37**
	(4,6)	(4,4)	(3,3)	(2,9)	(-16,8)	(-15,5)	(-5,0)	(-4,0)	(-15,8)	(-14,4)
SMB	0,08	0,07	**0,55**	**0,55**	**-0,36**	**-0,36**	-0,03	-0,03	**-0,50**	**-0,50**
	(1,8)	(1,7)	(12,4)	(12,0)	(-11,6)	(-11,4)	(-1,2)	(-1,4)	(-16,3)	(-15,9)
HML	**0,28**	**0,29**	**0,24**	**0,23**	**0,21**	**0,22**	-0,04	-0,03	**0,19**	**0,20**
	(4,9)	(4,9)	(3,9)	(3,7)	(4,8)	(4,9)	(-1,1)	(-1,0)	(4,5)	(4,6)
RMW	**0,50**	**0,48**	0,09	0,09	**0,56**	**0,52**	**0,12**	**0,12**	**0,67**	**0,64**
	(8,2)	(7,6)	(1,4)	(1,3)	(12,2)	(11,1)	(3,4)	(3,3)	(15,0)	(13,9)
CMA	**0,40**	**0,38**	0,12	0,11	**0,49**	**0,47**	**0,16**	**0,16**	**0,47**	**0,45**
	(4,6)	(4,3)	(1,3)	(1,2)	(7,4)	(7,1)	(3,3)	(3,3)	(7,4)	(7,1)
REV	-0,06	-0,06	0,02	0,02	**0,18**	**0,19**	**0,36**	**0,36**	-0,02	-0,02
	(-1,5)	(-1,6)	(0,6)	(0,6)	(6,3)	(6,6)	(16,4)	(16,5)	(-0,6)	(-0,6)
Adjusted R2	0,24	0,25	0,31	0,32	0,74	0,74	0,34	0,34	0,78	0,78
# obs	684	684	684	684	684	684	684	684	684	684

Table VIII
Economic Drivers of the Low-Risk Effect (continued)

Panel B: Lottery Sales and Casino Profits

	BAB$_{t;t+1}$	BAB$_{t;t+1}$	BAC$_{t;t+1}$	BAC$_{t;t+1}$	LMAX$_{t;t+1}$	LMAX$_{t;t+1}$	SMAX$_{t;t+1}$	SMAX$_{t;t+1}$	IVOL$_{t;t+1}$	IVOL$_{t;t+1}$
Casino$_t$	-0,47		-0,43		0,49		-0,05		0,04	
	(-0,83)		(-0,65)		(1,74)		(-0,28)		(0,11)	
Casino$_{t+1}$ - Casino$_t$	-1,84		-0,79		**-2,68**		-0,59		**-2,42**	
	(-1,28)		(-0,48)		(-3,75)		(-1,37)		(-2,86)	
Lottery$_t$		0,00		0,00		0,00		0,00		0,00
		(0,50)		(0,48)		(0,91)		(1,02)		(-0,31)
Lottery$_{t+1}$ - Lottery$_t$		0,00		0,00		0,00		0,00		0,00
		(1,29)		(1,52)		(0,62)		(0,42)		(1,94)
Controls										
Mkt	**0,27**	**0,21**	0,14	**0,19**	**-0,32**	**0,50**	-0,02	**0,18**	**-0,29**	**0,48**
	(3,4)	(4,1)	(1,6)	(4,1)	(-8,1)	(12,9)	(-0,8)	(6,2)	(-6,2)	(11,9)
SMB	0,25	**0,67**	**0,80**	**0,88**	**-0,26**	**0,21**	0,03	-0,03	**-0,40**	**0,49**
	(2,0)	(9,8)	(5,4)	(14,3)	(-4,2)	(4,1)	(0,9)	(-0,7)	(-5,3)	(9,0)
HML	**0,47**	**0,16**	0,19	0,10	**0,22**	**-0,23**	0,01	**-0,17**	**0,22**	**-0,28**
	(3,3)	(2,0)	(1,2)	(1,4)	(3,1)	(-3,9)	(0,3)	(-3,8)	(2,7)	(-4,6)
RMW	**0,51**	**0,46**	-0,12	0,16	**0,79**	**-0,46**	**0,09**	**-0,16**	**0,91**	**-0,46**
	(3,8)	(4,6)	(-0,8)	(1,7)	(11,9)	(-6,2)	(2,3)	(-2,7)	(11,6)	(-5,8)
CMA	0,19	0,06	0,21	0,05	**0,41**	-0,03	0,04	0,03	**0,46**	-0,08
	(0,9)	(0,5)	(0,9)	(0,5)	(4,0)	(-0,3)	(0,7)	(0,5)	(3,7)	(-0,9)
REV	-0,15	0,06	-0,01	0,03	**0,11**	**0,34**	**0,25**	**0,40**	-0,03	**0,19**
	(-1,4)	(0,9)	(-0,1)	(0,5)	(2,2)	(6,5)	(7,9)	(9,9)	(-0,4)	(3,3)
Adjusted R2	0,29	0,29	0,25	0,48	0,83	0,61	0,34	0,38	0,82	0,65
# obs	142	254	142	254	142	254	142	254	142	254

Panel C: CAPM alpha for portfolios sorted on mispricing and correlation

		Conditional sort on correlation					
		P1 (low)	P2	P3	P4	P5 (high)	LS
Sort on mispricing	P1 (low)	**0,6**	**0,5**	**0,4**	**0,3**	0,1	**-0,5**
		(5,5)	(5,2)	(4,6)	(3,8)	(1,8)	(-3,2)
	P2	**0,4**	**0,5**	**0,3**	0,2	0,0	**-0,4**
		(3,8)	(5,0)	(3,2)	(2,0)	(-0,4)	(-2,9)
	P3	**0,4**	**0,3**	0,1	0,1	-0,1	**-0,4**
		(3,4)	(2,7)	(1,1)	(1,7)	(-0,8)	(-2,8)
	P4	**0,3**	**0,2**	**0,2**	0,0	**-0,3**	**-0,6**
		(2,8)	(2,1)	(2,1)	(0,3)	(-3,6)	(-4,2)
	P5 (high)	-0,1	**-0,3**	**-0,3**	**-0,4**	**-0,7**	**-0,6**
		(-1,1)	(-2,1)	(-3,1)	(-2,9)	(-5,8)	(-3,1)
	LS	**-0,8**	**-0,8**	**-0,8**	**-0,7**	**-0,9**	
		(-6,3)	(-5,6)	(-5,6)	(-4,6)	(-5,3)	

Table IX
Horserace: Factors as Published

This table reports the result of regressing one low-risk factor on another, as well as control variables. Panel A reports the results for the U.S. sample and panel B reports the results for the global sample. The dependent variables are the monthly excess returns to betting against beta (BAB), betting against correlation (BAC), betting against volatility (BAV), the factor going long stocks with low maximum return over the past month (LMAX), the factor going long stocks with low maximum return scaled by volatility (SMAX), and the factor going long stocks with low idiosyncratic volatility (IVOL). The intercept alpha is in monthly percent. The control variables are the monthly excess return to the market portfolio (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and short-term reversal (REV). *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. The Sharpe ratio (SR) and information ratio (IR) are annualized.

	Panel A: U.S. Sample (1963 - 2015)					
	BAB	BAC	BAV	LMAX	SMAX	IVOL
Alpha	**0.31**	**0.62**	-0.23	0.05	**0.18**	0.08
	(3.04)	(5.05)	(-1.87)	(0.64)	(2.69)	(1.02)
MKT	**0.36**	**0.14**	**0.48**	**-0.42**	**-0.10**	**-0.38**
	(11.5)	(3.8)	(12.7)	(-22.2)	(-6.4)	(-18.6)
SMB	**0.34**	**0.63**	0.02	**-0.41**	-0.04	**-0.53**
	(8.2)	(12.6)	(0.4)	(-15.7)	(-1.9)	(-19.2)
HML	**0.13**	**0.14**	**0.14**	**0.10**	**-0.07**	**0.11**
	(2.6)	(2.4)	(2.4)	(2.7)	(-2.2)	(2.7)
RMW	0.07	-0.08	**0.43**	**0.39**	0.05	**0.55**
	(1.2)	(-1.1)	(5.9)	(9.9)	(1.6)	(13.1)
CMA	0.03	-0.06	-0.04	**0.35**	**0.11**	**0.38**
	(0.4)	(-0.7)	(-0.4)	(6.4)	(2.2)	(6.5)
REV	**-0.21**	**-0.14**	**-0.13**	**0.21**	**0.37**	0.00
	(-5.8)	(-3.3)	(-3.0)	(8.6)	(18.0)	(0.1)
BAB				**0.39**	**0.15**	**0.28**
				(15.4)	(7.0)	(10.3)
LMAX	**0.79**	**0.83**	**0.19**			
	(10.7)	(9.5)	(2.1)			
IVOL	-0.10	**-0.54**	**0.83**			
	(-1.4)	(-6.1)	(9.2)			
SR	0.90	0.93	0.27	0.34	0.78	0.22
IR	0.45	0.75	-0.28	0.10	0.40	0.15
R2	0.44	0.37	0.66	0.81	0.39	0.81
# obs	630	630	630	630	630	630

Table IX
Horserace: Factors as Published (continued)

	Panel B: Global Sample (1990 - 2015)					
	BAB	BAC	BAV	LMAX	SMAX	IVOL
Alpha	**0.21**	**0.37**	-0.17	-0.11	0.02	-0.09
	(1.98)	(2.98)	(-1.39)	(-1.33)	(0.24)	(-1.02)
MKT	**0.43**	**0.29**	**0.36**	**-0.44**	**-0.11**	**-0.34**
	(11.2)	(6.5)	(8.6)	(-19.4)	(-5.4)	(-13.6)
SMB	**0.72**	**0.79**	0.06	**-0.50**	-0.04	**-0.64**
	(12.2)	(11.6)	(0.9)	(-11.7)	(-1.1)	(-13.6)
HML	**0.16**	0.09	**0.24**	0.01	0.02	-0.01
	(2.5)	(1.2)	(3.3)	(0.2)	(0.3)	(-0.1)
RMW	**0.20**	0.17	-0.03	**0.42**	0.08	**0.49**
	(2.1)	(1.6)	(-0.2)	(6.3)	(1.3)	(6.7)
CMA	**-0.19**	-0.06	**-0.33**	**0.49**	0.09	**0.57**
	(-2.1)	(-0.5)	(-3.1)	(7.7)	(1.5)	(8.1)
REV	**-0.24**	**-0.11**	**-0.21**	**0.24**	**0.40**	**0.10**
	(-5.8)	(-2.3)	(-4.6)	(8.7)	(15.5)	(3.2)
BAB				**0.47**	**0.15**	**0.41**
				(14.0)	(4.9)	(10.8)
LMAX	**0.85**	**0.86**	**0.27**			
	(7.4)	(6.5)	(2.1)			
IVOL	-0.02	**-0.56**	**0.91**			
	(-0.2)	(-4.3)	(7.3)			
SR	0.92	0.89	0.33	0.34	0.43	0.35
IR	0.43	0.65	-0.30	-0.29	0.05	-0.22
R2	0.64	0.44	0.77	0.88	0.51	0.85
# obs	306	306	306	306	306	306

Table X
Turnover

This table reports the turnover of the different trading strategies considered in the paper. We measure turnover as the amount of dollars that has to be traded in each trading strategy on a monthly basis. BAC and BAV: At the beginning of each month stocks are ranked in ascending order based on the estimate of volatility (correlation) at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are assigned to one of two portfolios: low correlation (volatility) and high correlation (volatility). In these portfolios, stocks are weighted by ranked correlation (volatility) (lower correlation (volatility) stocks have larger weights in the low-correlation (volatility) portfolios and larger correlation (volatility) stocks have larger weights in the high-correlation (volatility) portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. Within each volatility (correlation) quintile, a self-financing portfolio is made that is long the low-correlation (volatility) portfolio and short the high-correlation (volatility) portfolio. Betting against correlation (volatility) is the equal-weighted average of these five portfolios. This table shows regression results for monthly returns to LMAX, SMAX, and IVOL. Panel A reports the results from the U.S. sample and Panel B reports the results from the global sample. LMAX (SMAX, IVOL) is constructed as the intersection of six value-weighted portfolios formed on size and MAX (SMAX, IVOL). For U.S. securities, the size breakpoint is the median NYSE market equity. For International securities, the size breakpoint is the 80th percentile by country. The MAX (SMAX, IVOL) breakpoints are the 30th and 70th percentile. We use unconditional sorts in the U.S. and conditional sorts in the international sample (first we sort on size and then MAX (SMAX, IVOL)). Firms are assigned to one of six portfolios based on these breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. LMAX (SMAX, IVOL) is then the average return to the two low-MAX (SMAX, IVOL) portfolios minus the average return to the two high-MAX (SMAX, IVOL) portfolios. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's lagged total market capitalization. MAX is the sum of the five highest returns over the previous month. SMAX is the MAX characteristic divided by one-year daily volatility. The IVOL factor is based on the characteristics defined by Ang, Hodrick, Xing, and Zhang (2006). The U.S. sample is form 1926-2015.

	Portfolio										
	HML	BAB	BAB	BAB	BAC	BAV	LMAX	SMAX	IVOL	LMAX(1Y)	SMAX(1Y)
Method	FF: june update	FF: june update	FF: monthly	Rank weights	Rank weights	Rank weights	FF: monthly	FF: monthly	FF: monthly	FF: monthly	FF: monthly
Turnover	0.24	0.21	0.41	0.34	0.35	0.36	2.06	2.77	1.76	0.46	1.14
Period over which the characteristics are calculated	NA	1 to 5 years	1 to 5 years	1 to 5 years	1 to 5 years	1 to 5 years	1 month	1 to 12 months	1 month	1 year	1 year

Table XI
MAX Factors Based on Yearly Look-Back Periods

This table shows regression results for monthly returns to LMAX and SMAX factors that are produced based on yearly estimates of MAX. Panel A reports the results from the long U.S. sample and Panel B reports the results from the global sample. LMAX 1-year (SMAX 1-year) is constructed as the intersection of six value-weighted portfolios formed on size and MAX 1-year (SMAX 1-year). For U.S. securities, the size breakpoint is the median NYSE market equity. For International securities, the size breakpoint is the 80th percentile by country. The MAX 1-year (SMAX 1-year) breakpoints are the 30th and 70th percentile. We use unconditional sorts in the U.S. and conditional sorts in the international sample (first we sort on size and then MAX 1-year (SMAX 1-year)). Firms are assigned to one of six portfolios based on these breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. LMAX 1-year (SMAX 1-year) is then the average return to the two low- MAX 1-year (SMAX 1-year) portfolios minus the average return to the two high-MAX (SMAX 1-year) portfolios. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's lagged total market capitalization. MAX 1-year is the sum of the 20 highest returns over the previous year. SMAX 1-year is the MAX 1-year characteristic divided by one-year daily volatility. The explanatory variables are monthly excess to the value-weighted market portfolio and the monthly returns for the SMB, HML, RMW, CMA, REV, and BAB factor. SMB, HML, RMW, and CMA are from Fama and French (2015). BAB is from Frazzini and Pedersen (2014). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1963 - 2015)					
	LMAX(1Y)	LMAX(1Y)	LMAX(1Y)	SMAX(1Y)	SMAX(1Y)	SMAX(1Y)
Alpha	**0.40**	0.09	-0.11	-0.13	**-0.25**	**-0.23**
	(3.73)	(0.89)	(-1.26)	(-1.67)	(-3.57)	(-3.25)
MKT	**-0.50**	**-0.43**	**-0.47**	0.00	**-0.05**	**-0.04**
	(-19.6)	(-17.5)	(-21.9)	(0.0)	(-2.6)	(-2.4)
SMB	**-0.67**	**-0.54**	**-0.59**	**-0.23**	**-0.21**	**-0.21**
	(-18.8)	(-16.0)	(-19.9)	(-9.1)	(-8.8)	(-8.6)
HML	**0.36**	**0.11**	0.00	**0.16**	**0.17**	**0.18**
	(9.2)	(2.3)	(-0.1)	(5.8)	(4.8)	(5.1)
RMW		**0.61**	**0.42**		**0.17**	**0.19**
		(12.3)	(9.4)		(4.8)	(5.2)
CMA		**0.52**	**0.37**		-0.07	-0.05
		(7.4)	(5.9)		(-1.3)	(-1.0)
REV		0.04	**0.06**		**0.25**	**0.25**
		(1.2)	(2.3)		(10.9)	(10.8)
BAB			**0.41**			-0.04
			(14.5)			(-1.8)
SR	0.07	0.07	0.07	-0.22	-0.22	-0.22
IR	0.53	0.13	-0.19	-0.24	-0.52	-0.48
R2	0.68	0.75	0.81	0.18	0.34	0.34
# obs	630	630	630	630	630	630

Table XI
MAX Factors Based on Yearly Look-Back Periods (continued)

	Panel B: Global Sample (1990 - 2015)					
	LMAX(1Y)	LMAX(1Y)	LMAX(1Y)	SMAX(1Y)	SMAX(1Y)	SMAX(1Y)
Alpha	**0.34**	-0.15	**-0.26**	**-0.19**	**-0.29**	**-0.27**
	(2.57)	(-1.32)	(-2.93)	(-2.08)	(-3.40)	(-3.26)
MKT	**-0.63**	**-0.40**	**-0.45**	-0.01	-0.04	-0.04
	(-20.9)	(-12.5)	(-18.3)	(-0.4)	(-1.9)	(-1.6)
SMB	**-0.57**	**-0.31**	**-0.59**	**-0.28**	**-0.24**	**-0.21**
	(-9.1)	(-5.7)	(-12.6)	(-6.5)	(-6.0)	(-4.8)
HML	**0.49**	0.05	-0.10	**0.22**	**0.23**	**0.24**
	(8.6)	(0.7)	(-1.9)	(5.5)	(4.4)	(4.7)
RMW		**0.92**	**0.44**		**0.20**	**0.26**
		(10.9)	(6.0)		(3.3)	(3.7)
CMA		**0.69**	**0.50**		-0.07	-0.04
		(7.7)	(7.1)		(-1.0)	(-0.7)
REV		0.04	**0.07**		**0.28**	**0.27**
		(1.0)	(2.4)		(9.7)	(9.6)
BAB			**0.54**			-0.06
			(14.4)			(-1.7)
SR	0.17	0.17	0.17	-0.27	-0.27	-0.27
IR	0.52	-0.29	-0.64	-0.42	-0.74	-0.71
R2	0.68	0.79	0.87	0.21	0.42	0.42
# obs	306	306	306	306	306	306

Table XII

Horserace: Factors based on Fama-French Methodology

This table reports regression results of horseraces where factors are constructed following the Fama and French (1993) methodology. Panel A reports the results for the U.S. sample and panel B reports the results for the global sample. The dependent variables are the monthly returns BAB, BAC, BAV, LMAX, SMAX, SMAX 1-year, and IVOL. All factors are constructed following the same methodology. BAB, for example, is constructed as the intersection of six value-weighted portfolios formed on size and beta. For U.S. securities, the size breakpoint is the median NYSE market equity. For International securities, the size breakpoint is the 80th percentile by country. The beta breakpoints are the 30th and 70th percentile. We use unconditional sorts in the U.S. and conditional sorts in the international sample (first we sort on size and then beta). Firms are assigned to one of six portfolios based on these breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. BAB is then the average return to the two low-BAB portfolios minus the average return to the two high-BAB portfolios. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's lagged total market capitalization. All factors are set up such they have positive CAPM alpha. For BAC and BAV, we create a factor within each volatility (correlation) quintile, and the BAC (BAV) factor is then the averages of these five. MAX is the sum of the five highest returns over the previous month. SMAX is the MAX characteristic divided by one-year daily volatility. IVOL is the characteristics defined by Ang, Hodrick, Xing, and Zhang (2006). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1963 - 2015)									
	BAB	BAB	BAC	BAC	BAV	BAV	LMAX	SMAX	SMAX(1Y)	IVOL
Alpha	**0.20**	0.06	**0.19**	0.09	**0.36**	**0.26**	0.06	**0.21**	**-0.25**	0.06
	(3.23)	(0.87)	(2.01)	(1.01)	(4.67)	(3.01)	(1.05)	(3.18)	(-3.43)	(0.99)
MKT	**-0.18**	**-0.22**	**-0.15**	**-0.15**	**-0.14**	**-0.19**	-0.03	-0.01	**-0.06**	**-0.04**
	(-9.7)	(-10.0)	(-5.3)	(-5.4)	(-6.0)	(-7.2)	(-1.6)	(-0.5)	(-2.7)	(-2.1)
SMB	**0.12**	-0.03	**0.39**	**0.31**	**-0.28**	**-0.43**	**-0.14**	0.03	**-0.22**	**-0.31**
	(4.8)	(-1.1)	(10.2)	(8.8)	(-9.2)	(-13.2)	(-6.5)	(1.0)	(-8.6)	(-12.8)
HML	**0.09**	0.00	0.03	-0.04	0.03	-0.03	**0.09**	-0.05	**0.17**	**0.08**
	(2.9)	(-0.1)	(0.6)	(-0.8)	(0.8)	(-0.8)	(3.2)	(-1.7)	(5.0)	(2.7)
RMW	**-0.15**	**-0.13**	**-0.15**	**-0.16**	**0.09**	**0.13**	**0.32**	0.07	**0.18**	**0.46**
	(-4.3)	(-3.1)	(-2.9)	(-3.1)	(2.0)	(2.8)	(10.5)	(1.9)	(5.0)	(13.7)
CMA	-0.07	-0.05	-0.11	-0.12	-0.05	-0.01	**0.25**	**0.11**	-0.06	**0.27**
	(-1.4)	(-1.0)	(-1.5)	(-1.7)	(-0.9)	(-0.2)	(5.8)	(2.2)	(-1.1)	(5.6)
REV	**-0.09**	**-0.23**	**-0.17**	**-0.26**	-0.01	**-0.11**	**0.22**	**0.37**	**0.25**	0.01
	(-4.5)	(-9.6)	(-5.7)	(-8.4)	(-0.3)	(-3.9)	(11.8)	(17.7)	(10.8)	(0.7)
BAB							**0.62**	**0.14**	-0.03	**0.54**
							(28.9)	(5.7)	(-1.1)	(22.5)
LMAX(1Y)	**0.91**		**0.54**		**0.73**					
	(36.0)		(14.4)		(23.7)					
LMAX		**0.92**		**0.60**		**0.70**				
		(28.9)		(14.3)		(18.2)				
SR	0.11	0.11	0.13	0.13	0.21	0.21	0.34	0.78	-0.22	0.22
IR	0.47	0.13	0.30	0.15	0.69	0.45	0.16	0.47	-0.51	0.15
R2	0.91	0.88	0.56	0.56	0.86	0.83	0.89	0.37	0.34	0.88
# obs	630	630	630	630	630	630	630	630	630	630

Table XII
Horserace: Factors based on Fama-French Methodology (continued)

	Panel B: Global Sample (1990 - 2015)									
	BAB	BAB	BAC	BAC	BAV	BAV	LMAX	SMAX	SMAX(1Y)	IVOL
Alpha	0.09	-0.03	0.01	-0.06	**0.29**	**0.19**	0.02	0.06	0.06	**-0.29**
	(1.29)	(-0.40)	(0.16)	(-0.66)	(3.86)	(2.33)	(0.25)	(0.76)	(0.76)	(-3.44)
MKT	**-0.14**	**-0.12**	-0.03	-0.03	**-0.16**	**-0.16**	**-0.06**	-0.01	-0.01	**-0.07**
	(-5.7)	(-4.4)	(-1.0)	(-0.9)	(-6.4)	(-5.6)	(-2.9)	(-0.3)	(-0.3)	(-2.5)
SMB	**0.19**	**0.16**	**0.45**	**0.42**	**-0.38**	**-0.41**	**-0.20**	0.05	0.05	**-0.25**
	(5.3)	(4.2)	(9.7)	(8.9)	(-9.9)	(-10.1)	(-6.6)	(1.4)	(1.4)	(-6.1)
HML	**-0.11**	**-0.21**	**-0.14**	**-0.19**	0.00	-0.07	**0.19**	0.07	0.07	**0.22**
	(-2.6)	(-4.5)	(-2.4)	(-3.3)	(0.0)	(-1.4)	(5.0)	(1.6)	(1.6)	(4.3)
RMW	0.04	0.04	0.03	0.06	0.00	0.03	**0.29**	0.07	0.07	**0.26**
	(0.6)	(0.6)	(0.4)	(0.7)	(-0.1)	(0.4)	(5.5)	(1.1)	(1.1)	(3.7)
CMA	0.02	0.00	0.04	0.05	-0.04	-0.04	**0.24**	0.03	0.03	-0.03
	(0.4)	(-0.0)	(0.5)	(0.6)	(-0.7)	(-0.5)	(4.6)	(0.4)	(0.4)	(-0.4)
REV	**-0.10**	**-0.26**	**-0.19**	**-0.28**	-0.01	**-0.14**	**0.25**	**0.40**	**0.40**	**0.27**
	(-4.0)	(-9.7)	(-5.9)	(-8.3)	(-0.5)	(-4.8)	(11.8)	(15.7)	(15.7)	(9.5)
BAB							**0.66**	**0.18**	**0.18**	-0.06
							(22.8)	(5.2)	(5.2)	(-1.6)
LMAX(1Y)	**0.89**		**0.55**		**0.73**					
	(24.6)		(12.0)		(19.3)					
LMAX		**0.96**		**0.57**		**0.75**				
		(22.8)		(10.8)		(16.5)				
SR	0.15	0.15	0.09	0.09	0.30	0.30	0.34	0.43	0.43	-0.27
IR	0.28	-0.09	0.03	-0.14	0.84	0.51	0.05	0.16	0.16	-0.75
R2	0.92	0.91	0.72	0.71	0.90	0.89	0.93	0.52	0.52	0.42
# obs	306	306	306	306	306	306	306	306	306	306

Table XIII
Horserace: Rank-Weighted Factors

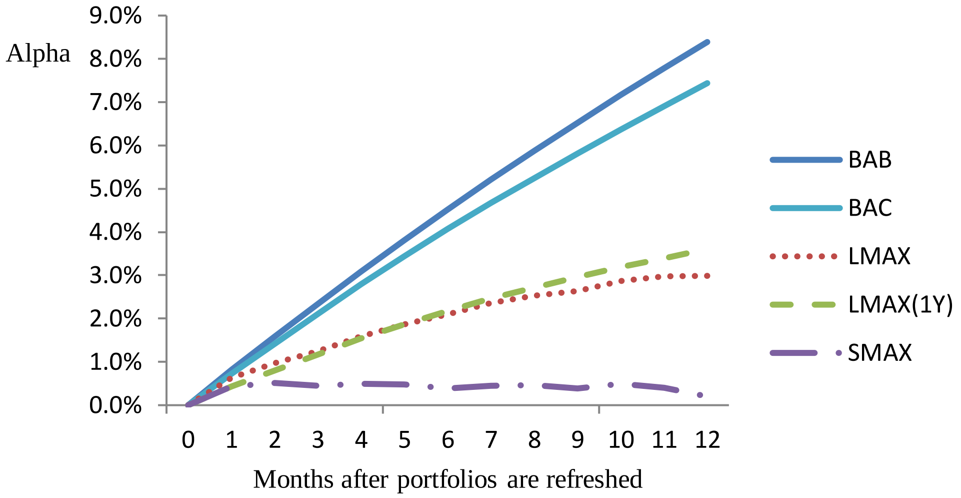
This table reports regression results of horseraces where all factors are rank-weighted. The dependent variables are the monthly returns BAB, BAC, BAV, LMAX, SMAX, and IVOL. All factors are constructed following the same methodology. BAB, for example, is constructed as follows: All stocks are sorted into two groups based on size. The size breakpoint is the median NYSE market equity. Within each size group, stocks are assigned to one of two portfolios: low beta and high beta. In these portfolios, stocks are weighted by rank (lower beta stocks have larger weights in the low-beta portfolios and larger beta stocks have larger weights in the high-beta portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. A self-financing portfolio is made that is long the low-beta portfolio and short the high-beta portfolio. All factors are set up such they have positive CAPM alpha. MAX is the sum of the five highest returns over the previous month. SMAX is the MAX characteristic divided by one-year daily volatility. IVOL is the characteristics defined by Ang, Hodrick, Xing, and Zhang (2006). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1952 - 2015)											
	BAB	BAB	BAC	BAC	BAV	BAV	LMAX	LMAX	SMAX	SMAX	IVOL	IVOL
Alpha	**0.32**	**0.24**	**0.27**	**0.24**	0.02	**-0.10**	0.14	-0.10	**0.22**	0.14	0.14	-0.05
	(3.34)	(3.29)	(3.56)	(3.33)	(0.16)	(-2.25)	(1.26)	(-1.12)	(2.84)	(1.90)	(1.56)	(-0.80)
MKT	0.02	**0.06**	-0.01	0.01	**-0.05**	0.01	**-0.08**	**-0.09**	**-0.04**	**-0.05**	**-0.06**	**-0.07**
	(1.0)	(3.7)	(-0.4)	(0.6)	(-2.1)	(1.1)	(-2.8)	(-4.5)	(-2.4)	(-2.8)	(-2.8)	(-4.6)
SMB	**0.14**	**0.15**	**0.36**	**0.37**	**-0.17**	**-0.16**	-0.02	**-0.12**	**0.09**	**0.06**	**-0.15**	**-0.24**
	(8.1)	(11.2)	(25.8)	(27.4)	(-9.5)	(-20.3)	(-0.8)	(-7.4)	(6.4)	(4.0)	(-9.5)	(-18.7)
HML	**0.33**	**0.31**	**0.20**	**0.19**	**0.24**	**0.22**	0.03	**-0.21**	**-0.12**	**-0.20**	**0.17**	-0.03
	(7.7)	(9.4)	(5.8)	(5.9)	(5.6)	(11.4)	(0.7)	(-5.2)	(-3.6)	(-5.9)	(4.3)	(-0.8)
RMW	**0.49**	**-0.12**	**0.12**	**-0.12**	**1.05**	**0.16**	**1.12**	**0.75**	**0.43**	**0.31**	**0.96**	**0.67**
	(14.7)	(-3.1)	(4.7)	(-3.3)	(30.5)	(7.7)	(28.5)	(21.9)	(16.3)	(11.0)	(31.1)	(25.2)
CMA	0.02	**-0.18**	-0.10	**-0.18**	**0.34**	0.05	**0.36**	**0.35**	0.11	0.10	**0.31**	**0.30**
	(0.2)	(-2.9)	(-1.6)	(-3.0)	(4.1)	(1.4)	(3.9)	(4.9)	(1.7)	(1.7)	(4.3)	(5.4)
REV	-0.01	**-0.15**	**-0.05**	**-0.10**	**0.05**	**-0.15**	**0.25**	**0.27**	**0.37**	**0.37**	-0.02	-0.01
	(-0.6)	(-7.7)	(-2.5)	(-5.3)	(2.2)	(-12.8)	(8.9)	(12.0)	(18.9)	(20.0)	(-0.7)	(-0.4)
BAB								**0.75**		**0.24**		**0.59**
								(22.7)		(8.7)		(23.8)
LMAX		**0.54**		**0.22**		**0.79**						
		(22.7)		(9.3)		(57.4)						
SR	0.83	0.83	0.78	0.78	0.33	0.33	0.68	0.68	1.17	1.17	0.36	0.36
IR	0.48	0.48	0.52	0.48	0.02	-0.33	0.18	-0.16	0.41	0.28	0.23	-0.12
R2	0.44	0.67	0.51	0.56	0.79	0.96	0.65	0.79	0.45	0.50	0.79	0.88
# obs	762	762	762	762	762	762	762	762	762	762	761	761

Figure I
Cumulative Alpha for Longer Holding Periods

This figure shows cumulative alpha for trading strategies in event time. The event time is months after the characteristics were last refreshed.

Panel A: Cumulative Three Factor Alpha



Panel B: Cumulative Five Factor Alpha

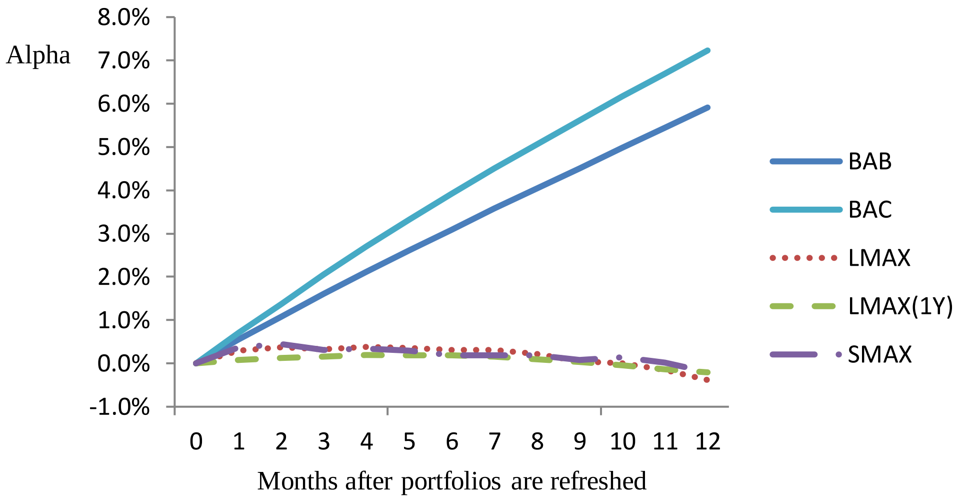


Table A1
Betting Against Volatility – Three Factor Alphas

This table shows returns to the betting against volatility factor in each correlation quintile, along with the equal-weighted average of these factors, which constitute our overall BAV factor. Panel A reports the BAV performance in the U.S. sample and panel B reports the performance in the global sample. At the beginning of each month stocks are ranked in ascending order based on the estimate of correlation at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are assigned to one of two portfolios: low volatility and high volatility. In these portfolios, stocks are weighted by ranked volatility (lower volatility stocks have larger weights in the low- volatility portfolios and larger volatility stocks have larger weights in the high- volatility portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. Within each correlation quintile, a self-financing BAC portfolio is made that is long the low-correlation portfolio and short the high-correlation portfolio. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's total (lagged) market capitalization. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB and HML factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. '$ long' and '$ short' measures how many dollars the betting against correlation portfolio is long and short. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1963-2015)					
Correlation quintile	1	2	3	4	5	BAV
Excess return	-0.10	**0.63**	**0.59**	**0.57**	0.30	**0.40**
	(-0.31)	(2.68)	(2.76)	(3.20)	(1.93)	(1.99)
Alpha	0.07	**0.57**	**0.54**	**0.55**	**0.30**	**0.40**
	(0.23)	(2.65)	(2.90)	(3.74)	(2.51)	(2.40)
MKT	**-0.16**	0.07	0.04	0.01	0.00	-0.01
	(-2.3)	(1.3)	(1.0)	(0.4)	(0.03)	(-0.2)
SMB	**-0.97**	**-0.67**	**-0.69**	**-0.65**	**-0.65**	**-0.73**
	(-10.2)	(-9.3)	(-11.1)	(-13.3)	(-16.5)	(-12.9)
HML	**0.49**	**0.60**	**0.61**	**0.53**	**0.50**	**0.55**
	(4.8)	(7.8)	(9.1)	(9.9)	(11.9)	(9.0)
SR	-0.04	0.37	0.38	0.44	0.27	0.27
IR	0.03	0.37	0.41	0.53	0.35	0.34
R2	0.22	0.21	0.27	0.34	0.44	0.32
# obs	630	630	630	630	630	630

	Panel B: Global Sample (1990-2015)					
Correlation quintile	1	2	3	4	5	BAV
Excess return	-0.06	**0.53**	**0.58**	**0.52**	**0.35**	0.38
	(-0.18)	(2.08)	(2.44)	(2.51)	(1.98)	(1.68)
Alpha	-0.16	**0.41**	**0.48**	**0.48**	**0.31**	0.31
	(-0.57)	(1.98)	(2.62)	(2.97)	(2.30)	(1.73)
MKT	**-0.27**	**-0.21**	**-0.26**	**-0.29**	**-0.25**	**-0.26**
	(-4.2)	(-4.4)	(-6.3)	(-7.8)	(-8.21)	(-6.4)
SMB	**-1.04**	**-0.68**	**-0.62**	**-0.54**	**-0.45**	**-0.67**
	(-7.8)	(-6.8)	(-7.0)	(-7.0)	(-7.1)	(-7.9)
HML	**0.85**	**0.79**	**0.77**	**0.62**	**0.56**	**0.72**
	(6.9)	(8.6)	(9.5)	(8.8)	(9.5)	(9.3)
SR	-0.04	0.41	0.48	0.50	0.39	0.33
IR	-0.12	0.40	0.53	0.60	0.46	0.35
R2	0.33	0.35	0.41	0.42	0.45	0.42
# obs	306	306	306	306	306	306

Table A2
Betting Against Volatility – Five Factor Alphas

This table shows returns to the betting against volatility factor in each correlation quintile, along with the equal-weighted average of these factors, which constitute our overall BAV factor. Panel A reports the BAV performance in the U.S. sample and panel B reports the performance in the global sample. At the beginning of each month stocks are ranked in ascending order based on the estimate of correlation at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are assigned to one of two portfolios: low volatility and high volatility. In these portfolios, stocks are weighted by ranked volatility (lower volatility stocks have larger weights in the low- volatility portfolios and larger volatility stocks have larger weights in the high- volatility portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. Within each correlation quintile, a self-financing BAC portfolio is made that is long the low-correlation portfolio and short the high-correlation portfolio. We form one set of portfolios in each country and compute global portfolios by weighting each country's portfolio by the country's total (lagged) market capitalization. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML, RMW, and CMA factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. '$ long' and '$ short' measures how many dollars the betting against correlation portfolio is long and short. Sharpe ratios and information ratios are annualized.

	Panel A: U.S. Sample (1963-2015)					
Correlation quintile	1	2	3	4	5	BAV
Excess return	-0.10	**0.63**	**0.59**	**0.57**	0.30	**0.40**
	(-0.31)	(2.68)	(2.76)	(3.20)	(1.93)	(1.99)
Alpha	-0.48	0.04	0.06	0.17	-0.03	-0.05
	(-1.77)	(0.18)	(0.35)	(1.26)	(-0.32)	(-0.34)
MKT	-0.05	**0.19**	**0.15**	**0.10**	**0.08**	**0.09**
	(-0.7)	(3.9)	(3.6)	(3.0)	(3.02)	(2.6)
SMB	**-0.65**	**-0.39**	**-0.43**	**-0.44**	**-0.48**	**-0.48**
	(-7.0)	(-5.8)	(-7.4)	(-9.7)	(-13.3)	(-9.3)
HML	**0.29**	**0.28**	**0.37**	**0.34**	**0.30**	**0.31**
	(2.2)	(3.0)	(4.5)	(5.3)	(6.0)	(4.4)
RMW	**1.43**	**1.23**	**1.17**	**0.94**	**0.76**	**1.11**
	(10.5)	(12.3)	(13.8)	(14.0)	(14.2)	(14.6)
CMA	**0.41**	**0.67**	**0.51**	**0.40**	**0.42**	**0.48**
	(2.1)	(4.7)	(4.3)	(4.2)	(5.6)	(4.5)
SR	-0.04	0.37	0.38	0.44	0.27	0.27
IR	-0.26	0.03	0.05	0.18	-0.05	-0.05
R2	0.33	0.36	0.44	0.50	0.58	0.49
# obs	630	630	630	630	630	630

Table A2 (continued)
Betting Against Volatility – Five Factor Alphas

	Panel B: Global Sample (1990-2015)					
Correlation quintile	1	2	3	4	5	BAV
Excess return	-0.06	**0.53**	**0.58**	**0.52**	**0.35**	0.38
	(-0.18)	(2.08)	(2.44)	(2.51)	(1.98)	(1.68)
Alpha	**-0.62**	-0.05	-0.01	-0.07	-0.19	-0.19
	(-2.16)	(-0.23)	(-0.07)	(-0.46)	(-1.67)	(-1.12)
MKT	-0.06	0.00	-0.03	-0.03	-0.02	-0.03
	(-0.8)	(-0.0)	(-0.7)	(-0.8)	(-0.63)	(-0.6)
SMB	**-0.80**	**-0.44**	**-0.35**	**-0.25**	**-0.18**	**-0.40**
	(-5.7)	(-4.3)	(-4.1)	(-3.5)	(-3.3)	(-4.9)
HML	**0.56**	**0.46**	**0.39**	**0.21**	**0.20**	**0.37**
	(3.2)	(3.6)	(3.6)	(2.4)	(2.9)	(3.6)
RMW	**0.97**	**0.93**	**0.99**	**1.09**	**1.01**	**1.00**
	(4.6)	(6.0)	(7.4)	(10.1)	(11.8)	(8.0)
CMA	0.41	**0.49**	**0.58**	**0.61**	**0.53**	**0.52**
	(1.8)	(3.0)	(4.1)	(5.3)	(5.8)	(4.0)
SR	-0.04	0.41	0.48	0.50	0.39	0.33
IR	-0.47	-0.05	-0.01	-0.10	-0.36	-0.24
R2	0.37	0.42	0.51	0.58	0.63	0.53
# obs	306	306	306	306	306	306

Table A3
Correlation vs. Volatility: Using FF-Betas

This table shows properties of 25 portfolios of U.S. stocks from 1926 to 2015. At the beginning of each calendar month, stocks are sorted first on ex ante volatility and then conditionally on ex ante correlation. Specifically, the stocks are assigned to one of five volatility quintiles based on NYSE breakpoints. Within each quintile, stocks are assigned to one of five correlation quintile portfolios based on NYSE breakpoints. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. The long-short portfolios are self-financing portfolios that are long $1 in the portfolio with highest correlation (volatility) within each volatility (correlation) quintile and short $1 in the portfolio with lowest correlation (volatility) within the same volatility (correlation) quintiles. Volatility is monthly volatility measured on a five-year rolling window. Correlation is estimated as the Dimson (1979) beta divided by the volatility of the stock and multiplied by the volatility of the market. The beta is estimated in a five-year rolling regression on monthly data. Panel A reports CAPM betas and Panel B reports CAPM alphas, i.e., respectively the slope and intercept in a regression of monthly excess return on excess returns to the CRSP value-weighted market portfolio (MKT). Panel B reports three-factor alphas, i.e., the intercept in a regression of monthly excess return on MKT, size (SMB), and value (HML) factors of Fama and French (1993). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates and 5% statistical significance is indicated in bold.

US 1930-2015

Panel A: CAPM beta

Sort on volatility	Conditional sort on correlation: P1 (low)	P2	P3	P4	P5 (high)	LS
P1 (low)	**0.5**	**0.7**	**0.7**	**0.8**	**0.9**	**0.3**
						(19.0)
P2	**0.8**	**1.0**	**1.0**	**1.1**	**1.1**	**0.4**
						(17.3)
P3	**0.9**	**1.1**	**1.1**	**1.3**	**1.4**	**0.5**
						(18.4)
P4	**0.9**	**1.1**	**1.3**	**1.4**	**1.5**	**0.6**
						(17.6)
P5 (high)	**1.0**	**1.2**	**1.3**	**1.5**	**1.7**	**0.7**
						(17.2)
LS	**0.5**	**0.6**	**0.6**	**0.8**	**0.8**	

US 1930-2015

Panel B: CAPM alpha

Sort on volatility	Conditional sort on correlation: P1 (low)	P2	P3	P4	P5 (high)	LS
P1 (low)	**0.3**	**0.2**	**0.1**	**0.2**	**0.1**	**-0.2**
	(4.0)	(2.0)	(2.1)	(2.6)	(2.0)	(-2.3)
P2	**0.3**	**0.2**	**0.2**	0.1	0.0	**-0.3**
	(3.0)	(2.5)	(2.3)	(1.0)	(-0.5)	(-2.7)
P3	0.2	0.1	0.0	-0.1	-0.1	**-0.4**
	(1.9)	(0.6)	(0.4)	(-0.8)	(-1.8)	(-2.6)
P4	0.2	0.1	0.0	-0.1	**-0.2**	**-0.4**
	(1.3)	(0.5)	(0.4)	(-1.0)	(-2.0)	(-2.2)
P5 (high)	0.0	-0.1	-0.1	-0.1	**-0.4**	**-0.4**
	(0.2)	(-0.3)	(-0.9)	(-0.6)	(-2.7)	(-2.1)
LS	-0.3	-0.2	-0.3	-0.3	**-0.5**	
	(-1.4)	(-1.1)	(-1.5)	(-1.4)	(-2.9)	

Table A3
Correlation vs. Volatility: Using FF-Betas (Continued)

US 1930-2015

Panel C: Three-factor alpha

		Conditional sort on correlation					
		P1 (low)	P2	P3	P4	P5 (high)	LS
Sort on volatility	P1 (low)	**0.3**	0.1	**0.1**	**0.2**	**0.1**	-0.2
		(3.9)	(1.6)	(2.2)	(2.7)	(2.7)	(-1.9)
	P2	**0.2**	0.1	0.1	0.0	0.0	**-0.3**
		(2.4)	(1.5)	(1.7)	(0.3)	(-0.7)	(-2.4)
	P3	0.1	0.0	-0.1	**-0.2**	**-0.2**	**-0.3**
		(1.2)	(-0.5)	(-0.8)	(-2.0)	(-2.6)	(-2.5)
	P4	0.0	-0.1	-0.1	**-0.2**	**-0.3**	**-0.4**
		(0.3)	(-0.6)	(-1.0)	(-2.5)	(-3.2)	(-2.1)
	P5 (high)	-0.2	-0.2	**-0.3**	-0.2	**-0.5**	-0.3
		(-1.2)	(-1.1)	(-2.3)	(-1.8)	(-3.8)	(-1.6)
	LS	**-0.5**	-0.3	**-0.4**	**-0.4**	**-0.7**	
		(-2.9)	(-1.7)	(-2.9)	(-2.6)	(-4.2)	

Table A4
Betting Against Correlation Using FF-Betas

This table shows returns to the betting against correlation (BAC) factor in each volatility quintile, along with the equal-weighted average of these factors, which constitute our overall BAC factor. At the beginning of each month stocks are ranked in ascending order based on the estimate of volatility at the end of the previous month. The ranked stocks are assigned to one of five quintiles. U.S. sorts are based on NYSE breakpoints. Within each quintile, stocks are assigned to one of two portfolios: low correlation and high correlation. In these portfolios, stocks are rank-weighted by correlation (lower correlation stocks have larger weights in the low-correlation portfolios and larger correlation stocks have larger weights in the high-correlation portfolios), and the portfolios are rebalanced every calendar month. The portfolios are (de)levered to have a beta of one at formation. Within each volatility quintile, a self-financing BAC portfolio is made that is long the low-correlation portfolio and short the high-correlation portfolio. Volatility is monthly volatility measured on a five-year rolling window. Correlation is estimated as the Dimson (1979) beta divided by the volatility of the stock and multiplied by the volatility of the market. The beta is estimated in a five-year rolling regression on monthly data. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML, RMW, and CMA factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. '$ long' and '$ short' measures how many dollars the betting against correlation portfolio is long and short. Sharpe ratios and information ratios are annualized.

	U.S. Sample (1963-2015)					
Volatility quintile	1	2	3	4	5	BAC
Excess return	**0.24**	**0.33**	**0.53**	**0.74**	**0.56**	**0.48**
	(2.76)	(3.46)	(4.62)	(5.25)	(2.70)	(4.46)
Alpha	**0.23**	**0.24**	**0.38**	**0.57**	**0.44**	**0.37**
	(3.08)	(2.85)	(3.52)	(4.38)	(2.32)	(3.91)
MKT	**-0.19**	**-0.11**	-0.03	0.05	**0.12**	-0.03
	(-10.2)	(-5.4)	(-1.3)	(1.7)	(2.7)	(-1.4)
SMB	**0.27**	**0.40**	**0.39**	**0.49**	**0.63**	**0.44**
	(10.4)	(13.9)	(10.7)	(10.9)	(9.8)	(13.4)
HML	**0.17**	**0.13**	**0.25**	**0.22**	0.10	**0.17**
	(4.7)	(3.2)	(4.9)	(3.6)	(1.1)	(3.8)
RMW	**-0.11**	-0.03	-0.04	**-0.18**	**-0.42**	**-0.16**
	(-2.9)	(-0.8)	(-0.8)	(-2.8)	(-4.4)	(-3.3)
CMA	0.00	0.01	-0.01	-0.03	-0.11	-0.03
	(0.0)	(0.2)	(-0.2)	(-0.3)	(-0.8)	(-0.4)
SR	0.38	0.48	0.64	0.72	0.37	0.61
IR	0.45	0.41	0.51	0.64	0.34	0.57
R2	0.31	0.28	0.21	0.24	0.25	0.30
# obs	630	630	630	630	630	630

Table A5

The Low-Risk Effect without Overpriced High-IVOL Stocks: Using FF-Betas

This table the results of factor regression for ten beta-sorted portfolios based on a subset of U.S. stocks from 1965 to 2015. At the beginning of each month, we rank all stocks in descending order based on their estimated beta at the end of the previous month. Following Liu Stambaugh and Yu (2017), we delete from the CRSP universe the stocks that are both in the top quintile of their mispricing measure and have IVOL in the top quartile of the distribution. The ranked stocks are sorted into decile portfolios based on NYSE breakpoints. The portfolios are value-weighted based on the market capital at the end of the previous month and they are rebalanced and refreshed every calendar month. The long-minus-short portfolio is long $1 in the high-beta portfolio and short $1 in the low-beta portfolio. The ex ante beta is estimated in a five-year rolling regression on monthly data following Dimson (1979). CAPM alpha is the intercept in a regression of monthly excess return where the explanatory variable is the excess return to the CRSP value-weighted market portfolio. The three-factor alpha is the intercept in a regression where the explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML of Fama and French (1993). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

US sample (1965-2015)	1 (low beta)	2	3	4	5	6	7	8	9	10 (high beta)	LS
Excess return	**0.44**	**0.54**	**0.51**	**0.51**	**0.61**	**0.54**	**0.52**	**0.51**	0.53	0.54	0.10
	(3.03)	(3.54)	(3.15)	(2.98)	(3.31)	(2.69)	(2.40)	(2.15)	(1.94)	(1.61)	(0.34)
CAPM alpha	0.18	**0.21**	0.14	0.11	**0.16**	0.04	-0.02	-0.09	-0.14	-0.26	**-0.43**
	(1.66)	(2.37)	(1.74)	(1.38)	(2.27)	(0.59)	(-0.29)	(-1.24)	(-1.42)	(-1.74)	(-1.98)
FF3 alpha	0.02	0.14	0.08	0.04	0.10	-0.02	-0.08	-0.11	-0.10	-0.14	-0.17
	(0.25)	(1.76)	(1.14)	(0.58)	(1.51)	(-0.27)	(-1.08)	(-1.61)	(-1.11)	(-1.23)	(-0.94)
Mkt	**0.63**	**0.76**	**0.84**	**0.91**	**0.98**	**1.08**	**1.13**	**1.20**	**1.27**	**1.44**	**0.81**
	(27.17)	(39.83)	(49.60)	(54.59)	(60.85)	(69.56)	(67.37)	(73.24)	(62.49)	(51.97)	(19.01)
SMB	**-0.07**	**-0.24**	**-0.19**	**-0.17**	**-0.10**	**-0.05**	0.02	**0.16**	**0.35**	**0.59**	**0.66**
	(-2.14)	(-9.13)	(-7.96)	(-7.20)	(-4.53)	(-2.37)	(0.85)	(7.08)	(12.24)	(15.20)	(11.10)
HML	**0.38**	**0.26**	**0.20**	**0.21**	**0.18**	**0.15**	**0.12**	-0.01	**-0.24**	**-0.49**	**-0.86**
	(10.73)	(8.93)	(7.63)	(8.48)	(7.18)	(6.48)	(4.84)	(-0.31)	(-7.76)	(-11.59)	(-13.46)
SR	0.43	0.50	0.44	0.42	0.47	0.38	0.34	0.30	0.27	0.23	0.05
R vol	0.08	0.07	0.06	0.06	0.06	0.05	0.06	0.06	0.07	0.10	0.15
IR	0.04	0.25	0.16	0.08	0.22	-0.04	-0.16	-0.23	-0.16	-0.18	-0.14
R^2	0.56	0.73	0.81	0.84	0.87	0.90	0.90	0.92	0.90	0.88	0.65
Obs	604	604	604	604	604	604	604	604	604	604	604

Table A6

The Low-Risk Effect without Overpriced High-IVOL Stocks: Using FP-Betas

This table the results of factor regression for ten beta-sorted portfolios based on a subset of U.S. stocks from 1965 to 2015. At the beginning of each month, we rank all stocks in descending order based on their estimated beta at the end of the previous month. Following Liu Stambaugh and Yu (2017), we delete from the CRSP universe the stocks that are both in the top quintile of their mispricing measure and have IVOL in the top quartile of the distribution. The ranked stocks are sorted into decile portfolios based on NYSE breakpoints. The portfolios are value-weighted based on the market capital at the end of the previous month and they are rebalanced and refreshed every calendar month. The long-minus-short portfolio is long $1 in the high-beta portfolio and short $1 in the low-beta portfolio. The ex ante beta is estimated following the method in Frazzini and Pedersen (2014). CAPM alpha is the intercept in a regression of monthly excess return where the explanatory variable is the excess return to the CRSP value-weighted market portfolio. The three-factor alpha is the intercept in a regression where the explanatory variables are the monthly excess return to the CRSP value-weighted market portfolio and the monthly returns to the SMB, HML of Fama and French (1993). Returns and alphas are in monthly percent, *t*-statistics are shown in parenthesis below the coefficient estimates, and 5% statistical significance is indicated in bold. Sharpe ratios and information ratios are annualized.

US sample (1965-2015)	1 (low beta)	2	3	4	5	6	7	8	9	10 (high beta)	LS
Excess return	**0.59**	**0.59**	**0.60**	**0.53**	**0.64**	**0.50**	**0.52**	**0.44**	0.44	0.26	-0.33
	(3.88)	(4.23)	(4.13)	(3.39)	(3.84)	(2.78)	(2.67)	(2.02)	(1.75)	(0.83)	(-1.17)
CAPM alpha	**0.35**	**0.32**	**0.29**	**0.18**	**0.26**	0.07	0.05	-0.09	**-0.18**	**-0.49**	**-0.84**
	(2.85)	(3.36)	(3.34)	(2.18)	(3.13)	(0.93)	(0.63)	(-1.04)	(-2.13)	(-3.76)	(-4.04)
FF3 alpha	0.17	0.17	0.15	0.06	**0.16**	-0.02	-0.04	**-0.18**	**-0.22**	**-0.47**	**-0.63**
	(1.43)	(1.94)	(1.90)	(0.76)	(2.11)	(-0.23)	(-0.49)	(-2.24)	(-2.51)	(-3.83)	(-3.20)
Mkt	**0.55**	**0.63**	**0.70**	**0.80**	**0.88**	**0.94**	**1.02**	**1.14**	**1.27**	**1.43**	**0.89**
	(20.04)	(30.98)	(36.69)	(45.18)	(50.28)	(55.32)	(56.60)	(58.53)	(62.34)	(49.94)	(19.05)
SMB	**0.11**	-0.05	-0.03	**-0.07**	**-0.14**	**-0.11**	**-0.07**	-0.02	**0.06**	**0.37**	**0.25**
	(3.00)	(-1.88)	(-1.01)	(-2.75)	(-5.81)	(-4.43)	(-2.83)	(-0.72)	(2.14)	(9.14)	(3.88)
HML	**0.38**	**0.37**	**0.34**	**0.31**	**0.29**	**0.25**	**0.23**	**0.23**	0.06	**-0.19**	**-0.57**
	(9.24)	(12.00)	(11.69)	(11.53)	(10.80)	(9.52)	(8.45)	(7.82)	(1.81)	(-4.46)	(-8.16)
SR	0.55	0.60	0.58	0.48	0.54	0.39	0.38	0.29	0.25	0.12	-0.16
R vol	0.10	0.07	0.07	0.06	0.06	0.06	0.06	0.07	0.07	0.10	0.16
IR	0.21	0.28	0.27	0.11	0.30	-0.03	-0.07	-0.32	-0.36	-0.55	-0.46
R^2	0.44	0.62	0.70	0.78	0.81	0.84	0.85	0.86	0.88	0.85	0.53
Obs	604	604	604	604	604	604	604	604	604	604	604

Table A7
Correlation between MD and Other Measures of Funding Liquidity

U.S. 1963-2015, quarterly

Panel A: Levels

	MD	Ted Spread	Noise	Leverage
MD	1.000	-0.002	-0.079	0.032
Ted Spread	-0.002	1.000	0.631	-0.118
Noise	-0.079	0.631	1.000	-0.361
Leverage	0.032	-0.118	-0.361	1.000

Panel B: Changes

	ΔMD	ΔTed Spread	ΔNoise	ΔLeverage
ΔMD	1.000	-0.223	-0.229	0.255
ΔTed Spread	-0.223	1.000	0.465	-0.214
ΔNoise	-0.229	0.465	1.000	-0.452
ΔLeverage	0.255	-0.214	-0.452	1.000

Figure A1
State Dependent Performance of High- and Low-Beta Portfolios

This figure shows the average return to high- and low-beta portfolios in 20 different states based on the market return. In particular, we create 20 groups of monthly observations by sorting on the realized market return. For each quantile, we calculate the average excess return to the market portfolio and a high- and low-beta portfolio. The beta sorted portfolios are constructed as follows. At the beginning of each month, we rank stocks in ascending order based on their estimated market beta. The ranked stocks are assigned to one of ten portfolios based on NYSE breakpoints. Within each portfolio, stocks are value-weighted based on the market value at the end of the previous month. The low-beta portfolio is the portfolio with the lowest beta and the high-beta portfolio is the portfolio with the highest beta.

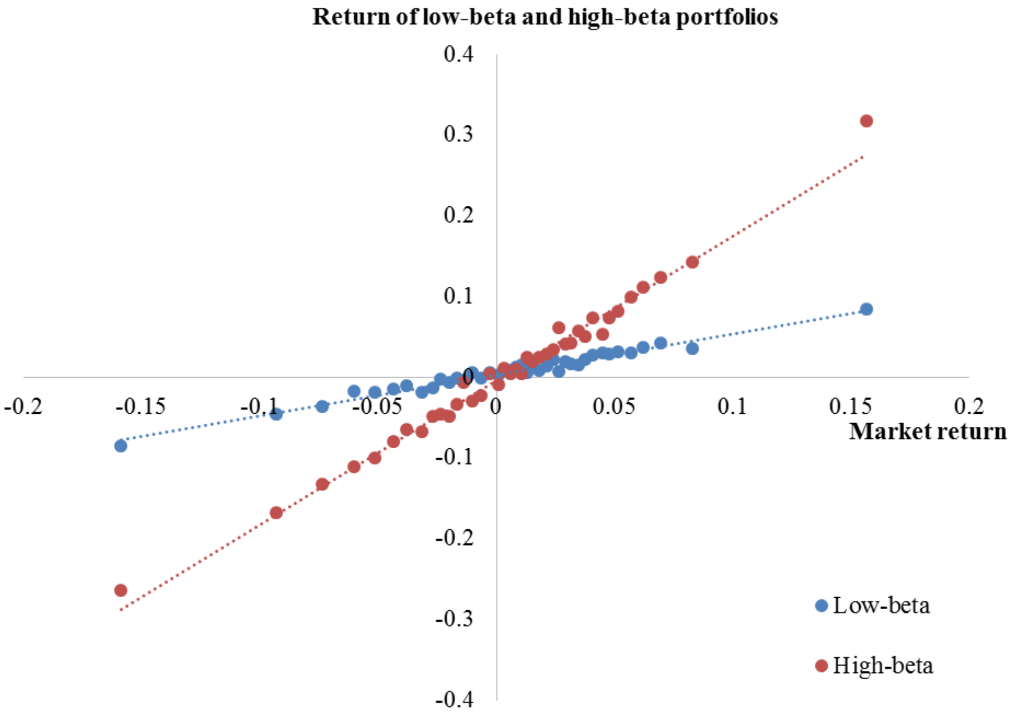


Figure A2
Realized and Required Return for Beta-Sorted Portfolios

This figure shows the realized and required return to beta-sorted portfolios using three different asset pricing models. The green dots show the average realized excess returns for ten beta-sorted portfolios (normalized by dividing by the average market excess return). The blue line shows the portfolio's required returns based on the CAPM (again normalized by dividing by the required market excess return). Likewise, the red and purple lines show the required returns implied by a stochastic discount factor (SDF) for the constant relative risk aversion (CRRA) investor with risk aversion of either $\gamma = 10$ (red line) or $\gamma = 3$ (purple), again normalized required market excess return. The beta sorted portfolios are constructed as follows. At the beginning of each month, we rank stocks in ascending order based on their estimated market beta. The ranked stocks are assigned to one of ten portfolios based on NYSE breakpoints. Within each portfolio, stocks are value-weighted based on the market value at the end of the previous month.