Journal of Financial Economics 135 (2020) 629–652

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Betting against correlation: Testing theories of the low-risk effect[☆]

Cliff Asness[a], Andrea Frazzini[a], Niels Joachim Gormsen[b,*], Lasse Heje Pedersen[a,c,d]

[a] *AQR Capital Management, LLC, Two Greenwich Plaza, Greenwich, CT 06830, USA*
[b] *University of Chicago, Booth School of Business, 5807 South Woodlawn Avenue, Chicago, IL 60637, USA*
[c] *Department of Finance, Copenhagen Business School, A4.12, Solbjerg Plads 3, 2000 Frederiksberg, Denmark*
[d] *Centre for Economic Policy Research (CEPR), London, UK*

ARTICLE INFO

Article history:
Received 29 June 2017
Revised 8 August 2018
Accepted 15 August 2018
Available online 12 July 2019

JEL classification:
G02
G12
G14
G15

Keywords:
Asset pricing
Leverage constraints
Lottery demand
Margin
Sentiment

ABSTRACT

We test whether the low-risk effect is driven by leverage constraints and, thus, risk should be measured using beta versus behavioral effects and, thus, risk should be measured by idiosyncratic risk. Beta depends on volatility and correlation, with only volatility related to idiosyncratic risk. We introduce a new betting against correlation (BAC) factor that is particularly suited to differentiate between leverage constraints and behavioral 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.

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, and about empirical asset pricing more broadly, is the observation that assets with low risk have high alpha, the so-called low-risk effect (Black et al., 1972).[1] 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 the low-risk effect is driven by leverage constraints and risk should be measured using systematic risk versus whether the low-risk effect is driven by behavioral effects and risk should be measured using

☆ We are grateful for helpful comments from Robin Greenwood, Toby Moskowitz, and Tatyana Marchuk (discussant) as well as from seminar participants at AQR Capital Management, BI-SHoF 2017 conference on asset pricing and financial econometrics, the Q-group spring 2017 seminar, Instinet Annual Global Quant Research Conference, Sanford C. Bernstein research conference on controversies in quantitative finance, and Copenhagen Business School. Niels Joachim Gormsen and Lasse Heje Pedersen gratefully acknowledge support from FRIC Center for Financial Frictions (grant no. DNRF102).

* Corresponding author.
E-mail address: niels.gormsen@chicagobooth.edu (N.J. Gormsen).

[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).

https://doi.org/10.1016/j.jfineco.2019.07.003
0304-405X/© 2019 Published by Elsevier B.V.

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 maximum return (SMAX), which 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. The systematic low-risk effect is thus based on a rigorous economic theory and has survived more than 40 years of out of sample evidence. Further, a number of papers find evidence consistent with the underlying economic mechanism of leverage constraints. Jylhä (2018) shows that exogenous changes in margin requirements influence the slope of the security market line; Boguth and Simutin (2018) show that funding constraints as proxied by mutual fund beta predict BAB; Malkhozov et al. (2016) show that international illiquidity predict BAB; and Adrian et al. (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 et al., 2007) and, therefore, the focus should be on idiosyncratic risk. Ang et al. (2006, 2009) find that stocks with low idiosyncratic volatility (IVOL) have high risk-adjusted returns in the US and internationally. In a similar vein, Bali et al. (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] Bali et al. (2017) argue that the low-risk effect is driven by idiosyncratic risk, not systematic risk. Also, Liu et al. (2018) propose that the low-risk effect is driven by idiosyncratic risk and appears only among overpriced stocks.

The challenge with the existing literature is that it seeks to run a horse race between factors that are, by construction, highly correlated because 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. 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 and betting against volatility (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. 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).

Because stocks with lower market correlations have lower market betas when holding volatility constant, 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 that BAC has a highly significant capital asset pricing model (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 et al. (2018), 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 and thus providing further evidence that the low-risk effect is not just about idiosyncratic risk or its interaction with mispricing. Mispricing predicts stock returns controlling for correlation, so leverage constraints do not explain all anomalies –a separate role appears to exist for other effects as considered by Liu et al. (2018).

Another challenge to the low-risk effect, both with systematic and idiosyncratic risk, is posed by Fama and French (2016) who argue that a five-factor model of the market (MKT), size (small minus big, SMB), value (high minus low, HML), profitability (roust minus weak, RMW), and investment (conservative minus aggressive, CMA) explains the low-risk effect (and the majority of the cross section of returns more broadly, except for momentum). While they do not test BAB explicitly, they suggest that no relationship exists between alpha and systematic risk once controlling for the five factors. We study this question explicitly, and we also control for short-term reversal (REV), which is particularly relevant for the idiosyncratic risk factors (due to their high turnover). 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 0.6% per month (t-statistic of 5.3) in the US and 0.4% in our global sample (t-statistic of 3.5).

Turning to the behavioral theory, we consider the factors that go long stocks with low MAX (LMAX) or low

[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). We also address this debate. We note that betting against beta (BAB) and betting against correlation (BAC) are based on equilibrium theories of asset pricing, while the other factors are ad hoc empirical specifications.

[3] See also the related evidence on corporate finance and banking (Baker and Wurgler, 2015; Baker et al., 2020), benchmark constraints (Brennan, 1993; Baker et al., 2011) and leverage constraints and differences of opinion (Hong and Sraer, 2016).

[4] See also the measure related to idiosyncratic skewness studied by Boyer et al. (2009).

[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, respectively, i.e., a small difference relative to the average cross-sectional standard deviation of MAX of 0.032.

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] Because 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 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 US, 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, none of the factors is 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 et al. (2018). We find that BAB and BAC are predicted by measures of leverage constraints and 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 US 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, consistent with theories of lottery demand. We find no evidence that higher sales of lottery tickets are associated with the return 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 horse-races between the different low-risk factors to judge their relative importance. We regress each type of low-risk factor (systematic or idiosyncratic) on the alternate type of low-risk factor as well as several controls (the Fama–French factors and short-term reversal). 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 (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 because 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 do not, however, rule out that lottery demand matters as we are controlling for many factors, some of which could themselves capture similar effects.

Finally, we address that the different factors we consider 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 in which 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. The factors based on idiosyncratic risk 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

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

[7] We also consider other alternative theories of the low-risk effect. The literature includes so-called money illusion as suggested by Modigliani and Cohn (1979) and studied by Cohen et al. (2005). We find no evidence that inflation predicts either BAB or BAC. This result holds despite the fact that we include the 1970s and 1980s, time periods that had large shocks to inflation.

[8] If behavioral investors naively look for lottery stocks, then perhaps the simplest way to do so would be to buy stocks from industries

Table 1
Summary statistics.
This table shows summary statistics as of June of each year. The sample includes all US common stocks [Center for Research in Security Prices (CRSP) shrcd equal to 10 or 11] and all global stocks (tcpi equal to 0) in the merged CRSP and Xpressfeed global databases.

Code	Country	Total number of stocks	Average number of stocks	Firm size (billion US dollars)	Weight in global portfolio	Start year	End year
AUS	Australia	3286	1027	0.61	0.018	1985	2015
AUT	Austria	217	84	0.82	0.002	1986	2015
BEL	Belgium	445	147	1.90	0.009	1986	2015
CAN	Canada	2106	576	1.20	0.022	1982	2015
CHE	Switzerland	596	226	3.72	0.024	1986	2015
DEU	Germany	2414	850	3.09	0.071	1986	2015
DNK	Denmark	411	156	1.01	0.004	1986	2015
ESP	Spain	415	147	3.65	0.015	1986	2015
FIN	Finland	307	117	1.32	0.004	1986	2015
FRA	France	1932	641	2.35	0.044	1986	2015
GBR	United Kingdom	6371	2013	1.63	0.102	1986	2015
GRC	Greece	425	186	0.40	0.002	1988	2015
HKG	Hong Kong	2510	816	1.50	0.030	1986	2015
IRL	Ireland	157	53	1.52	0.002	1986	2015
ISR	Israel	724	282	0.39	0.003	1994	2015
ITA	Italy	686	245	2.34	0.018	1986	2015
JPN	Japan	5309	3053	1.21	0.188	1986	2015
NLD	Netherlands	423	173	3.58	0.020	1986	2015
NOR	Norway	719	185	0.85	0.004	1986	2015
NZL	New Zealand	349	112	1.04	0.003	1986	2015
PRT	Portugal	157	63	1.56	0.002	1988	2015
SGP	Singapore	1259	474	0.71	0.011	1986	2015
SWE	Sweden	1201	309	1.44	0.012	1986	2015
USA	United States	24,218	3328	1.21	0.389	1926	2015

other factors and to using a lower turnover, and they are weaker globally. The 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.

The paper proceeds as follows. Section 2 covers data and methodology. Section 3 studies the systematic part of the low-risk effect. Section 4 studies the idiosyncratic part of the low-risk effect. Section 5 links the low-risk factors to economic drivers. Section 6 runs horse races between different low-risk factors. Section 7 concludes.

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 1. Stock returns are from the union of the Center for Research in Security Practices (CRSP) tape and the XpressFeed global database. All returns are in US dollars and do not include any currency hedging. Because all returns are in US dollars, all excess returns are measured as excess returns above the US Treasury bill rate.[9]

We divide stocks into a long US sample and a broad global sample. The US 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, with some factors available only from 1964 and onward.

Our broad global sample contains all available common stocks on the union of the CRSP tape and the XpressFeed global database. Table 1 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

We construct betting against correlation portfolios for each country. 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. US 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

with high skewness. However, the MAX factor does not work for industry selection (not reported here for brevity). In contrast, Asness et al. (2014) find that BAB works both within and across industries.

[9] Said differently, we consider the return to converting one US dollar into foreign currency, investing in foreign stocks, and then next period converting the proceeds back to US dollars, in excess of simply investing in US T-bills.

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

$$w_H^q = k^q \left(z^q - \overline{z^q}\right)^+ \tag{1}$$

and

$$w_L^q = k^q \left(z^q - \overline{z^q}\right)^-, \tag{2}$$

respectively, 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

$$r_{t+1}^{BAC(q)} = \frac{1}{\beta_t^{L,q}}\left(r_{t+1}^{L,q} - r^f\right) - \frac{1}{\beta_t^{H,q}}\left(r_{t+1}^{H,q} - r^f\right). \tag{3}$$

Here, r^f is the risk-free return, $r_{t+1}^{L,q} = r_{t+1}^{q'} w_L^q$ and $r_{t+1}^{H,q} = r_{t+1}^{q'} w_H^q$ are the returns of the low- and high-correlation portfolios, and $\beta_t^{L,q} = \beta_t^{q'} w_L^q$ and $\beta_t^{H,q} = \beta_t^{q'} w_H^q$ are the corresponding betas. The return to the final BAC factor is given by

$$r_{t+1}^{BAC} = \frac{1}{5}\sum_{q=1}^{5} r_{t+1}^{BAC(q)}. \tag{4}$$

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

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

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

$$r_{t+1}^{BAC,global} = \sum_{k=1}^{K} \frac{\pi_t^k}{\sum_j \pi_t^j} r_{t+1}^{BAC,k} \tag{6}$$

and

$$r_{t+1}^{BAV,global} = \sum_{k=1}^{K} \frac{\pi_t^k}{\sum_j \pi_t^j} r_{t+1}^{BAV,k}, \tag{7}$$

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):

$$\hat{\beta}_i^{TS} = \hat{\rho}_{i,m}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}, \tag{8}$$

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 toward 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). 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

To capture the behavioral explanations of the low-risk effect, we construct LMAX, SMAX, and IVOL factors. The LMAX factor is the negative of the FMAX factor introduced by Bali et al. (2017) to ensure that all factors are long low-risk stocks. 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:

$$r_{t+1}^{LMAX,global} = \sum_{k=1}^{K} \frac{\pi_t^k}{\sum_j \pi_t^j} r_{t+1}^{LMAX,k}. \tag{9}$$

The country-specific LMAX portfolios are constructed as the intersection of six value-weighted portfolios formed on size and MAX. For US securities, the size break-point is the median NYSE market equity. For international securities, the size break-point is the 80th percentile by country. The MAX break-points are the 30th and 70th percentile. We use unconditional sorts in the US 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 and large-cap and the low-MAX and small-cap portfolio returns minus the average of the high-MAX and large-cap and the high-MAX and 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). 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

[10] We use three-day overlapping returns to estimate correlations to account for nonsynchronous trading.

described in Section 2.1). We then compute the SMAX factor exactly as above but based on this scaled MAX characteristic instead of the standard MAX.

We construct IVOL factors based on the characteristic used in Ang et al. (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. For the US, we follow Ang et al. (2006) and use the market, size, and value portfolios of Fama and French (1993) as right-hand-side variables and, for outside the US, 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. We use their five-factor model based on the value-weighted market factor (MKT), size factor (SMB), value factor (HML), profitability factor (RMW), and investment factor (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 are available from 1959 to 2015 and they are 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 measure (*MD*):

$$MD_t = \frac{\text{Margin debt}_t}{\text{Market capitalization of NYSE firms}_t}. \tag{10}$$

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 Federal Reserve Economic Data (FRED) database.

We introduce two new measures of lottery demand. The first is a measure of casino profits in the US. It is the quarterly time series of profits for the casino industry scaled by nominal gross domestic product (GDP). The casino industry has the North American Industry Classification Code (NAICS) 713,210. 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. For 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 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. Proposition 1(ii) of Frazzini and Pedersen (2014) shows that the CAPM alpha of any security i is given by

$$\alpha_i = \psi(1-\beta_i) = \psi\left(1 - \frac{\rho_i \sigma_i}{\sigma_m}\right). \tag{11}$$

In other words, the alpha α_i decreases in its beta β_i, which in turn can be decomposed into volatility σ_i and market correlation ρ_i (while the Lagrange multiplier ψ and the market volatility σ_m are the same across stocks).

Hence, this theory predicts that both components of BAB, BAC and BAV, should deliver positive alphas because BAC varies correlation (holding volatility constant) and BAV varies volatility (holding correlation constant).

3.1. Double-sorting on correlation and volatility

Before we consider the actual factors, we examine a simple double sort of volatility and correlation. Table 2 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. 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 produces similar magnitudes of spreads in ex post betas. Because 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).

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

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

Table 2
Correlation versus Volatility: beta and risk-adjusted returns.
This table shows properties of 25 portfolios of US stocks from 1929 to 2015. At the beginning of each calendar month, stocks are sorted first on ex-ante volatility and then conditionally on ex-ante correlation. The stocks are assigned to one of five volatility quintiles based on NYSE break-points. Within each quintile, stocks are assigned to one of five correlation quintile portfolios based on NYSE break-points. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. The long-short (LS) 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 capital asset pricing model (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 Center for Research in Security Prices value-weighted market portfolio (MKT). Panel C reports three-factor alphas, i.e., the intercept in a regression of monthly excess return on MKT, size (SMB, small minus big), and value (HML, high minus low) factors of Fama and French (1993). Returns and alphas are in monthly percent, *t*-statistics are shown in parentheses below the coefficient estimates, and 5% statistical significance is indicated in bold.

	Conditional sort on correlation					
	P1 (low)	P2	P3	P4	P5 (high)	LS
Panel A: CAPM beta						
Sort on volatility						
P1 (low)	**0.4**	**0.6**	**0.7**	**0.8**	**0.9**	**0.4**
						(25.2)
P2	**0.7**	**0.9**	**1.0**	**1.1**	**1.2**	**0.5**
						(25.6)
P3	**0.7**	**1.0**	**1.2**	**1.3**	**1.4**	**0.7**
						(26.2)
P4	**0.8**	**1.0**	**1.2**	**1.3**	**1.6**	**0.8**
						(23.5)
P5 (high)	**0.8**	**1.0**	**1.2**	**1.3**	**1.6**	**0.8**
						(15.2)
LS	**0.4**	**0.5**	**0.5**	**0.5**	**0.7**	
	(8.7)	(13.1)	(15.9)	(17.1)	(21.3)	
Panel B: CAPM alpha						
Sort on volatility						
P1 (low)	**0.4**	**0.3**	**0.2**	0.1	**0.1**	**−0.3**
	(5.5)	(3.8)	(3.3)	(1.6)	(2.2)	(−3.7)
P2	**0.3**	**0.2**	0.1	0.0	−0.1	**−0.4**
	(3.6)	(2.1)	(1.6)	(0.3)	(−0.8)	(−3.2)
P3	**0.4**	**0.3**	0.0	−0.1	**−0.2**	**−0.6**
	(4.1)	(3.2)	(0.3)	(−0.6)	(−2.0)	(−4.1)
P4	**0.5**	**0.3**	0.0	−0.1	**−0.3**	**−0.7**
	(3.6)	(2.3)	(0.2)	(−0.8)	(−2.0)	(−4.2)
P5 (high)	0.3	0.0	0.0	−0.2	**−0.6**	**−0.8**
	(1.2)	(0.1)	(0.2)	(−1.3)	(−2.9)	(−3.3)
LS	−0.2	−0.2	−0.2	−0.3	**−0.7**	
	(−0.6)	(−1.1)	(−1.0)	(−1.7)	(−3.1)	
Panel C: Three-factor alpha						
Sort on volatility						
P1 (low)	**0.4**	**0.2**	**0.2**	0.1	**0.1**	**−0.3**
	(5.1)	(3.3)	(2.8)	(1.4)	(2.9)	(−3.2)
P2	**0.2**	0.1	0.1	−0.1	−0.1	**−0.3**
	(2.8)	(1.1)	(0.9)	(−0.9)	(−1.6)	(−3.1)
P3	**0.3**	0.2	−0.1	**−0.2**	**−0.3**	**−0.6**
	(3.3)	(1.9)	(−1.6)	(−2.8)	(−3.7)	(−4.5)
P4	**0.3**	0.1	−0.2	**−0.3**	**−0.5**	**−0.8**
	(2.6)	(0.9)	(−1.8)	(−2.8)	(−4.2)	(−4.5)
P5 (high)	0.0	−0.2	−0.2	**−0.5**	**−0.8**	**−0.8**
	(0.2)	(−1.2)	(−1.5)	(−3.6)	(−4.9)	(−3.3)
LS	−0.4	**−0.4**	**−0.4**	**−0.5**	**−0.9**	
	(−1.6)	(−2.4)	(−2.6)	(−3.6)	(−5.2)	

Panels B and C consider the risk-adjusted returns for these portfolios. Both the CAPM alpha (Panel B) and the three-factor alpha (Panel C) decrease as correlation or volatility increases. To examine the economic and statistical significance of these results, we consider the long/short portfolios in the right-most 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,

Table 3
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 US sample, and Panel B reports the results in the global sample. *t*-statistics are shown in parentheses below the coefficient estimates and 5% statistical significance is indicated in bold. The sample periods are 1930–2015 for the US sample and 1990–2015 for the Global sample.

	Dependent variable: BAB	
	US sample	Global sample
Intercept	0.00	0.00
	(0.05)	(0.96)
BAC	0.69	0.85
	(60.03)	(53.60)
BAV	**0.58**	**0.54**
	(63.45)	(52.86)
R^2	0.85	0.95
Number of observations	1020	306

we first show how BAB can be decomposed into BAC and BAV:

$$BAB_t = a_0 + a_1 BAC_t + a_2 BAV_t + \varepsilon_t. \tag{12}$$

Table 3 reports the result, showing that both BAC and BAV contribute to the return of the original BAB factor. In the US, BAB has a loading of 0.69 on BAC and 0.58 on BAV. The loadings in the global sample are 0.85 and 0.54. The *R*-squared of the regressions are 85% in the U.S. sample and 95% 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 4 reports the return and factor loadings of the BAC factor and its building blocks. We construct betting against correlation factors within each volatility quintile, and the overall BAC factor is the equal-weighted average of these five factors. Panel A shows the results in the US, 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 of Table 4 reports the analogous results in the global sample. 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, the loadings on RMW and CMA also tend to be positive, especially those of RMW. This is also expected because, as noted by Asness et al. (2019), 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 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 produce positive alphas relative to right-hand-side variables 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 five 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 because 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. In the US, 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: 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 and A4, we show 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 volatil-

[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 a perfect measure of cheapness is unavailable, 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 can also be explained by effects other than leverage constraints as we discuss further in Section 5.2.

Table 4
Betting against correlation (BAC).
This table shows returns to the betting against correlation 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 US 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. US sorts are based on NYSE break-points. 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 (small minus big), HML (high minus low), RMW (robust minus weak), and CMA (conservative minus aggressive) factors of Fama and French (2015). Returns and alphas are in monthly percent, *t*-statistics are shown in parentheses 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)	Volatility quintile					
	1	2	3	4	5	BAC
Excess return	**0.47**	**0.79**	**0.73**	**0.98**	**1.11**	**0.82**
	(3.60)	(5.84)	(5.36)	(6.66)	(5.11)	(6.14)
Alpha	**0.30**	**0.61**	**0.48**	**0.70**	**0.90**	**0.60**
	(2.69)	(5.36)	(4.10)	(5.12)	(4.31)	(5.25)
MKT	**−0.14**	**−0.10**	−0.03	0.03	0.05	−0.04
	(−5.2)	(−3.6)	(−1.2)	(0.9)	(0.89)	(−1.5)
SMB	**0.61**	**0.70**	**0.64**	**0.55**	**0.66**	**0.63**
	(15.7)	(17.9)	(15.9)	(11.8)	(9.2)	(16.2)
HML	**0.13**	**0.12**	**0.17**	**0.19**	**0.22**	**0.17**
	(2.4)	(2.3)	(3.0)	(2.9)	(2.2)	(3.1)
RMW	0.03	0.00	0.04	0.06	**−0.25**	−0.02
	(0.5)	(0.0)	(0.6)	(0.9)	(−2.3)	(−0.4)
CMA	0.10	0.04	0.11	0.14	0.03	0.08
	(1.2)	(0.5)	(1.3)	(1.5)	(0.2)	(1.0)
SR	0.50	0.81	0.74	0.92	0.71	0.85
IR	0.39	0.78	0.60	0.75	0.63	0.77
R^2	0.32	0.37	0.32	0.22	0.17	0.34
Number of observations	630	630	630	630	630	630
Panel B: Global sample (1990–2015)						
Excess return	0.24	**0.61**	**0.56**	**0.68**	**1.13**	**0.64**
	(1.91)	(4.31)	(3.75)	(4.04)	(4.75)	(4.75)
Alpha	0.14	**0.43**	**0.33**	**0.30**	**0.78**	**0.40**
	(1.23)	(3.58)	(2.42)	(1.98)	(3.48)	(3.47)
MKT	−0.03	0.03	**0.08**	**0.13**	**0.22**	**0.08**
	(−0.9)	(1.1)	(2.2)	(3.1)	(3.57)	(2.5)
SMB	**0.61**	**0.80**	**0.74**	**0.83**	**1.08**	**0.76**
	(11.0)	(13.9)	(11.2)	(11.2)	(10.0)	(13.7)
HML	**0.15**	**0.15**	0.15	**0.20**	0.02	0.13
	(2.1)	(2.1)	(1.8)	(2.1)	(0.2)	(1.8)
RMW	0.10	**0.26**	**0.32**	**0.54**	**0.43**	**0.36**
	(1.2)	(3.0)	(3.2)	(4.8)	(2.6)	(4.2)
CMA	0.04	−0.01	0.03	0.14	0.20	0.05
	(0.5)	(−0.1)	(0.2)	(1.2)	(1.2)	(0.5)
SR	0.38	0.85	0.74	0.80	0.94	0.94
IR	0.27	0.77	0.52	0.43	0.75	0.75
R^2	0.32	0.40	0.30	0.30	0.25	0.38
Number of observations	306	306	306	306	306	306

ity and lottery-like returns have low alpha. By idiosyncratic volatility, we refer to the idiosyncratic volatility characteristic defined by Ang et al. (2006), which is the monthly residual volatility in the Fama–French three-factor model as explained in Section 2. By lottery-like, we again refer to the MAX characteristic (Bali et al., 2011), which is the mean of the five highest daily returns over the last month as explained in Section 2, 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

Table 5
Scaled maximum return (SMAX) versus 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 US from 1927 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 break-points. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. The long-short (LS) 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) quintile. 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 capital assest pricing model (CAPM) alphas, Panel B reports three-factor alphas (MKT, market; SMB, small minus big; HML, high minus low) and Panel C reports five-factor alpha (MKT; SMB; HML; RMW, robust minus weak; CMA, conservative minus agressive). Alphas are in monthly percent, *t*-statistics are shown in parentheses below the coefficient estimates, and 5% statistical significance is indicated in bold.

	Conditional sort on SMAX					
	P1 (low)	P2	P3	P4	P5 (high)	LS
Panel A: CAPM alpha						
Sort on volatility						
P1 (low)	**0.4**	**0.2**	0.1	0.1	0.1	**−0.3**
	(5.4)	(3.1)	(1.4)	(2.0)	(1.1)	(−3.4)
P2	**0.3**	**0.2**	0.1	0.0	**−0.2**	**−0.5**
	(3.9)	(2.4)	(1.7)	(0.2)	(−2.8)	(−5.1)
P3	**0.3**	0.1	−0.1	−0.1	**−0.4**	**−0.7**
	(3.7)	(1.5)	(−1.3)	(−1.2)	(−3.6)	(−5.5)
P4	**0.4**	0.2	−0.1	**−0.3**	**−0.4**	**−0.9**
	(3.5)	(1.2)	(−1.0)	(−2.1)	(−3.7)	(−6.0)
P5 (high)	**0.4**	0.0	−0.1	**−0.5**	**−0.8**	**−1.2**
	(2.1)	(0.1)	(−0.7)	(−2.5)	(−3.9)	(−5.6)
LS	0.0	−0.2	−0.2	**−0.7**	**−0.9**	
	(0.2)	(−0.8)	(−1.0)	(−2.7)	(−3.8)	
Panel B: Three-factor alpha						
Sort on volatility						
P1 (low)	**0.3**	**0.2**	0.1	0.1	0.1	**−0.3**
	(5.5)	(3.2)	(1.0)	(1.9)	(1.0)	(−3.5)
P2	**0.2**	0.1	0.1	0.0	**−0.3**	**−0.5**
	(3.1)	(1.7)	(0.9)	(−0.7)	(−3.9)	(−5.1)
P3	**0.2**	0.0	**−0.2**	**−0.2**	**−0.5**	**−0.7**
	(2.9)	(0.2)	(−3.0)	(−2.7)	(−5.2)	(−5.7)
P4	**0.3**	0.0	**−0.3**	**−0.4**	**−0.6**	**−0.9**
	(3.0)	(−0.2)	(−2.5)	(−3.9)	(−5.6)	(−6.2)
P5 (high)	**0.4**	−0.1	−0.3	**−0.8**	**−1.0**	**−1.4**
	(2.3)	(−0.8)	(−1.9)	(−4.3)	(−5.4)	(−6.2)
LS	0.0	−0.3	**−0.4**	**−0.9**	**−1.0**	
	(0.2)	(−1.8)	(−2.0)	(−4.4)	(−5.2)	

leverage to a stock with low volatility and high scaled MAX. Hence, scaled MAX isolates what is different about the lottery demand.

Table 5 shows CAPM and three-factor alphas of 25 portfolios sorted first on volatility and then conditionally on scaled MAX. 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 and goes short 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 6 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 US and globally, the two factors combine to explain most of the variation in LMAX: the R-squared is 87% in the US and 97% globally with insignificant intercepts.

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

Table 7 reports the performance and factor exposures of the three idiosyncratic risk factors. The three factors have significant three-factor alphas. 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.

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 because LMAX and SMAX go long stocks with low returns on their best days. IVOL has little

Table 6
Low maximum return (LMAX) as scaled maximum return (SMAX) and betting against volatility (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 parentheses below the coefficient estimates, and 5% statistical significance is indicated in bold. The sample periods are 1927–2015 for the US sample and 1990–2015 for the Global sample.

	Dependent variable: BAB	
	US sample	Global sample
Intercept	0.00	0.00
	(−0.03)	(0.66)
SMAX	**0.70**	**0.48**
	(30.57)	(20.74)
TV	**0.63**	**0.71**
	(70.90)	(82.65)
R^2	0.87	0.97
Number of observations	1020	306

loading on REV (so excluding REV from the right-hand side hardly changes the results; not shown).

Panel B of Table 7 considers the three idiosyncratic factors 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. We note that the global sample is shorter so, it has less power to detect significant alphas.

In summary, the idiosyncratic risk factors LMAX, SMAX, and IVOL produce positive alphas in the US, but their five-factor alphas appear weak outside the US.

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 examine 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 predict each factor's alpha in excess of these factors, i.e., the parts of the return more unique to each factor. We test whether such discount rate shocks predict returns in line with the competing theories, assuming that expected cash flow shocks are held constant.

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 US government bonds as defined by Hu et al. (2013), and positively correlated with the leverage applied by financial intermediaries as seen in Appendix Table A7. 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 8 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 shift their portfolios toward low-risk stocks when leverage constraints decrease. This contemporaneous effect is statistically significant. In other words, because 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, not sentiment.

We next consider the determinants of the idiosyncratic risk factors, also reported in Panel A of Table 8. 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, none of the idiosyncratic factors LMAX, SMAX, and IVOL appears 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 the UK, which is the sample for our lottery ticket regressions.

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

Table 7
The idiosyncratic factors: low maximum return (LMAX), scaled maximum return (SMAX), and low idiosyncratic volatility (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 US 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, small minus big), value (HML, high minus low), profitability (RMW, robust minus weak), investment (CMA, conservative minus agressive), and short-term reversal (REV). *t*-statistics are shown in parentheses below the coefficient estimates, and 5% statistical significance is indicated in bold. The Sharpe ratio (SR) and information ratio (IR) are annualized.

	SMAX			LMAX			IVOL	
Panel A: U.S. sample (1963–2015)								
Alpha	**0.44**	**0.38**	**0.25**	**0.58**	**0.31**	**0.24**	**0.52**	**0.21**
	(5.59)	(4.77)	(3.68)	(5.81)	(3.34)	(2.63)	(5.23)	(2.38)
MKT	**−0.04**	−0.02	**−0.09**	**−0.42**	**−0.35**	**−0.39**	**−0.43**	**−0.35**
	(−2.0)	(−1.2)	(−5.4)	(−17.8)	(−15.8)	(−17.4)	(−18.1)	(−16.2)
SMB	−0.02	0.01	−0.02	**−0.48**	**−0.35**	**−0.37**	**−0.65**	**−0.50**
	(−0.7)	(0.3)	(−1.1)	(−14.3)	(−11.2)	(−12.0)	(−19.6)	(−16.8)
HML	**0.08**	0.04	−0.03	**0.45**	**0.24**	**0.21**	**0.42**	**0.19**
	(2.9)	(1.1)	(−0.8)	(12.7)	(5.5)	(4.8)	(11.6)	(4.6)
RMW		**0.12**	**0.12**		**0.57**	**0.57**		**0.68**
		(3.0)	(3.6)		(12.3)	(12.8)		(15.5)
CMA		0.08	**0.16**		**0.46**	**0.50**		**0.48**
		(1.4)	(3.4)		(6.9)	(7.8)		(7.6)
REV			**0.36**			**0.19**		0.00
			(16.9)			(6.6)		(−0.1)
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	0.35
R^2	0.03	0.04	0.34	0.64	0.72	0.73	0.69	0.77
Number of observations	630	630	630	630	630	630	630	630
Panel B: Global sample (1990–2015)								
Alpha	0.18	0.09	0.04	**0.45**	0.02	−0.01	**0.45**	−0.02
	(1.88)	(0.92)	(0.51)	(3.69)	(0.14)	(−0.14)	(3.74)	(−0.15)
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)	(−13.5)	(−18.5)	(−10.4)
SMB	−0.02	0.03	0.04	**−0.49**	**−0.26**	**−0.26**	**−0.68**	**−0.44**
	(−0.4)	(0.6)	(1.1)	(−8.4)	(−5.0)	(−5.1)	(−11.8)	(−8.7)
HML	**0.19**	**0.14**	0.06	**0.58**	**0.19**	**0.14**	**0.57**	0.12
	(4.4)	(2.3)	(1.3)	(10.7)	(2.8)	(2.3)	(10.7)	(1.8)
RMW		**0.19**	**0.22**		**0.83**	**0.85**		**0.86**
		(2.5)	(3.8)		(10.4)	(11.2)		(11.3)
CMA		0.06	**0.15**		**0.61**	**0.66**		**0.71**
		(0.8)	(2.4)		(7.2)	(8.2)		(8.7)
REV			**0.39**			**0.21**		**0.09**
			(14.5)			(6.0)		(2.5)
SR	0.41	0.41	0.41	0.34	0.34	0.34	0.35	0.35
IR	0.38	0.20	0.11	0.75	0.03	−0.03	0.76	−0.03
R^2	0.09	0.11	0.47	0.69	0.78	0.81	0.69	0.80
Number of observations	306	306	306	306	306	306	306	306

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 et al. (2018) propose that stocks with high idiosyncratic risk have higher average mispricings because 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 et al. (2018) double-sort stocks on beta and mispricing (using the mispricing measure of Stambaugh et al., 2015). They find that, when keeping mispricing constant, the relation between beta and three-factor alpha exists only among overpriced stocks (echoing a related finding in Stambaugh et al., 2015).

Our analysis differs from that of Liu et al. (2018) for several reasons. First, the theory of leverage constraints predicts that high-beta stocks endogenously become overpriced (relative to the standard CAPM) so the theory does not make clear predictions for the alpha-beta relation when controlling for overpricing, especially when one considers the three-factor alpha instead of the one-factor alpha (i.e., controlling for overpricing could throw the baby

Table 8
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 variables 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 one hundred 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 gross domestic product (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 Center for Research in Securities Prices value-weighted market portfolio and the monthly returns to the SMB (small minus big), HML (high minus low), RMW (robust minus weak), and CMA (conservative minus aggressive) 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 *Lottery* is on the right-hand side. Panel C uses the mispricing measure of Liu et al. (2018), returns and alphas are in monthly percent, *t*-statistics are shown in parentheses below the coefficient estimates, and 5% statistical significance is indicated in bold. LS = Long mins short portfolio.

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**	−0.31	**−0.66**		0.19		−0.03		0.12
	(−1.69)	(−2.78)	(−1.83)	(−3.21)		(1.16)		(−0.23)		(0.76)
$MD_{t+1}-MD_t$	**6.18**	**5.74**	**9.24**	**8.36**		−2.02		0.86		−1.96
	(3.55)	(3.17)	(5.64)	(4.91)		(−1.50)		(0.84)		(−1.49)
$SENT_t$		0.13		−0.05	**0.21**	0.17	0.09	0.07	**0.24**	**0.23**
		(1.09)		(−0.47)	(2.34)	(1.85)	(1.33)	(1.02)	(2.71)	(2.60)
$SENT_{t+1}$-$SENT_t$		1.07		0.87	0.58	0.72	**1.04**	**1.03**	0.02	0.13
		(1.33)		(1.14)	(0.97)	(1.20)	(2.27)	(2.24)	(0.04)	(0.22)
INF_t		**−0.10**		**−0.14**		−0.03		−0.03		0.02
		(−2.03)		(−3.02)		(−0.71)		(−1.19)		(0.67)
INF_{t+1}-INF_t		−0.30		−0.23		**−0.65**		−0.17		−0.38
		(−1.00)		(−0.82)		(−2.91)		(−1.00)		(−1.74)
Controls										
MKT	**0.16**	**0.16**	0.05	0.04	**−0.38**	**−0.41**	**−0.09**	**−0.08**	**−0.35**	**−0.37**
	(4.6)	(4.4)	(1.6)	(1.3)	(−16.8)	(−15.5)	(−5.0)	(−4.0)	(−15.8)	(−14.3)
SMB	0.08	0.07	**0.58**	**0.59**	**−0.36**	**−0.36**	−0.03	−0.03	**−0.50**	**−0.49**
	(1.8)	(1.7)	(14.9)	(14.5)	(−11.6)	(−11.4)	(−1.2)	(−1.4)	(−16.3)	(−15.8)
HML	**0.28**	**0.29**	**0.18**	**0.18**	**0.21**	**0.22**	−0.03	−0.03	**0.20**	**0.20**
	(4.9)	(4.9)	(3.4)	(3.3)	(4.8)	(4.9)	(−1.0)	(−0.9)	(4.7)	(4.7)
RMW	**0.50**	**0.48**	0.04	0.03	**0.56**	**0.52**	**0.12**	**0.12**	**0.67**	**0.64**
	(8.2)	(7.6)	(0.7)	(0.5)	(12.3)	(11.1)	(3.4)	(3.3)	(15.0)	(13.9)
CMA	**0.40**	**0.38**	0.12	0.11	**0.48**	**0.46**	**0.16**	**0.16**	**0.46**	**0.45**
	(4.6)	(4.3)	(1.5)	(1.4)	(7.4)	(7.1)	(3.3)	(3.3)	(7.3)	(7.0)
REV	−0.06	−0.06	0.02	0.02	**0.18**	**0.19**	**0.36**	**0.36**	−0.01	0.00
	(−1.5)	(−1.6)	(0.6)	(0.6)	(6.3)	(6.6)	(16.4)	(16.4)	(−0.2)	(−0.2)
R^2	0.24	0.25	0.37	0.38	0.74	0.74	0.34	0.34	0.78	0.78
Number of observations	684	684	684	684	684	684	684	684	684	684

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		0.01	
	(−0.83)		(−0.64)		(1.71)		(−0.26)		(0.04)	
$Casino_{t+1}$ - $Casino_t$	−1.84		−0.74		**−2.67**		−0.59		**−2.39**	
	(−1.28)		(−0.44)		(−3.74)		(−1.36)		(−2.84)	
$Lottery_t$		0.00		0.00		0.00		0.00		0.00
		(0.64)		(0.51)		(0.39)		(−0.43)		(0.76)
$Lottery_{t+1}$ - $Lottery_t$		0.00		0.00		0.00		0.00		0.00
		(1.08)		(1.24)		(−0.31)		(−0.21)		(−1.21)
Controls										
MKT	**0.27**	**0.21**	0.15	**0.19**	**−0.32**	**−0.46**	−0.02	**−0.18**	**−0.29**	**−0.46**
	(3.4)	(4.2)	(1.6)	(4.2)	(−8.1)	(−11.6)	(−0.8)	(−6.1)	(−6.1)	(−11.2)
SMB	0.25	**0.64**	**0.80**	**0.86**	**−0.27**	**−0.22**	0.04	0.01	**−0.40**	**−0.52**
	(2.0)	(9.9)	(5.4)	(14.3)	(−4.2)	(−4.2)	(0.9)	(0.3)	(−5.3)	(−9.7)
HML	**0.47**	−0.05	0.20	−0.04	**0.22**	0.11	0.01	**0.13**	**0.24**	**0.11**
	(3.3)	(−0.7)	(1.2)	(−0.7)	(3.1)	(1.9)	(0.4)	(3.0)	(3.0)	(2.0)
RMW	**0.51**	**0.48**	−0.12	**0.19**	**0.79**	**0.49**	**0.10**	**0.13**	**0.91**	**0.43**
	(3.8)	(5.4)	(−0.8)	(2.4)	(11.8)	(7.0)	(2.4)	(2.5)	(11.7)	(5.9)
CMA	0.19	0.15	0.21	0.07	**0.41**	**0.18**	0.04	0.00	**0.44**	**0.27**
	(0.9)	(1.4)	(0.8)	(0.7)	(3.9)	(2.1)	(0.7)	(−0.1)	(3.6)	(2.9)
REV	−0.15	0.01	−0.02	0.00	**0.11**	**−0.36**	**0.25**	**−0.41**	−0.01	**−0.21**
	(−1.4)	(0.2)	(−0.2)	(−0.0)	(2.2)	(−6.4)	(7.8)	(−9.8)	(−0.2)	(−3.6)
R^2	0.29	0.30	0.25	0.47	0.83	0.60	0.33	0.36	0.81	0.64
Number of observations	142	252	142	252	142	252	142	252	142	252

Table 8
(*continued*)

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**	**0.4**	0.1	**−0.5**
		(5.5)	(5.3)	(4.6)	(4.2)	(1.5)	(−3.4)
	P2	**0.4**	**0.4**	**0.3**	0.2	0.0	**−0.5**
		(3.9)	(4.8)	(3.2)	(1.9)	(−0.3)	(−3.0)
	P3	**0.4**	**0.2**	0.2	0.1	−0.1	**−0.4**
		(3.3)	(2.5)	(1.8)	(1.6)	(−0.9)	(−2.7)
	P4	**0.3**	0.1	**0.2**	0.0	**−0.3**	**−0.6**
		(2.9)	(1.5)	(2.6)	(−0.2)	(−3.3)	(−4.0)
	P5 (high)	−0.1	**−0.2**	**−0.4**	**−0.4**	**−0.7**	**−0.5**
		(−1.1)	(−2.0)	(−3.5)	(−3.3)	(−5.6)	(−2.9)
	LS	**−0.8**	**−0.8**	**−0.8**	**−0.8**	**−0.8**	
		(−6.3)	(−5.6)	(−6.0)	(−5.2)	(−5.1)	

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 (because 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 mispricing, 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 mechanically picking up the effect of idiosyncratic volatility. Panel C of Table 8 reports the results. Consistent with the theory of leverage constraints, higher correlation leads to lower alpha irrespective of the degree of over- or under-pricing (looking across each row). 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. We note that, while sorting on correlation does not mechanically sort on IVOL, it also does not hold IVOL constant (and doing so is cumbersome, as it would require triple-sorted portfolios). That said, IVOL varies only modestly across the portfolios and it falls with correlation (across each row), so the alternative behavioral theories cannot explain the low alpha of the high-correlation portfolios.

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 et al. (2018) 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. This finding arises because of their specific measures of alpha and beta and because of their sample. 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 and risky stocks 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, 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 an effect of beta only 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 and 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 the idea that stocks can be mispriced due to other effects consistent with Stambaugh et al. (2015) and Liu et al. (2018). The evidence based on deleting certain stocks provides further evidence of the robustness of the low-risk effect, although certain subsamples and certain measures of beta and alpha also exist in which the effect is weaker.

5.3. Alternative economic drivers

5.3.1. Money illusion

To test the Modigliani–Cohn hypothesis of money illusion as proposed in this connection by Cohen et al. (2005), we include inflation in Table 8, 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.

5.3.2. Skewness and co-skewness

The CAPM is based on specific assumptions, in particular, that the representative investor has quadratic utility, implying that required returns depend only on the covariance (or beta) with the market return. 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 toward skew risk because this utility functions puts additional emphasis

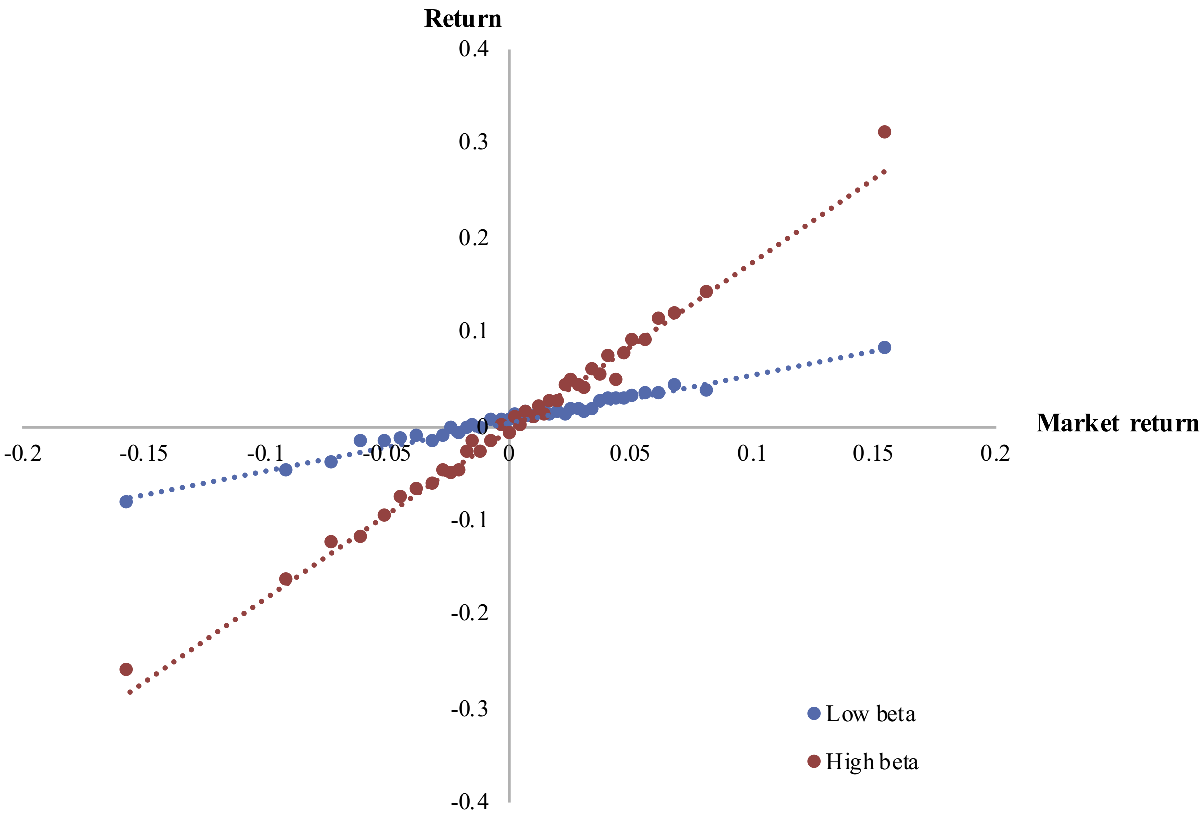

Fig. 1. State dependent performance of high- and low-beta portfolios.
This figure shows the average return to high- and low-beta portfolios in 20 different states based on the market return. We create 20 groups of monthly observations by sorting on the realized market return. For each quantile, we calculate 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 break-points. 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.

on the worst states of the market (Kraus and Litzenberger, 1976). Schneider et al. (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. Fig. 1 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% 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 leveraged to the same skew risk.

Further, Fig. 1 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 nonlinearity in the most extreme cases. In the worst market outcomes, low-beta stocks perform slightly worse than implied by their beta and the reverse is true for high-beta stocks. This finding is consistent with the loading on the squared market return shown by Schneider et al. (2016). Therefore, skew risk 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?

Fig. 2 plots the required return to ten beta-sorted portfolios as implied by three different asset pricing models: the CAPM, a CRRA investor with risk aversion of 3, and

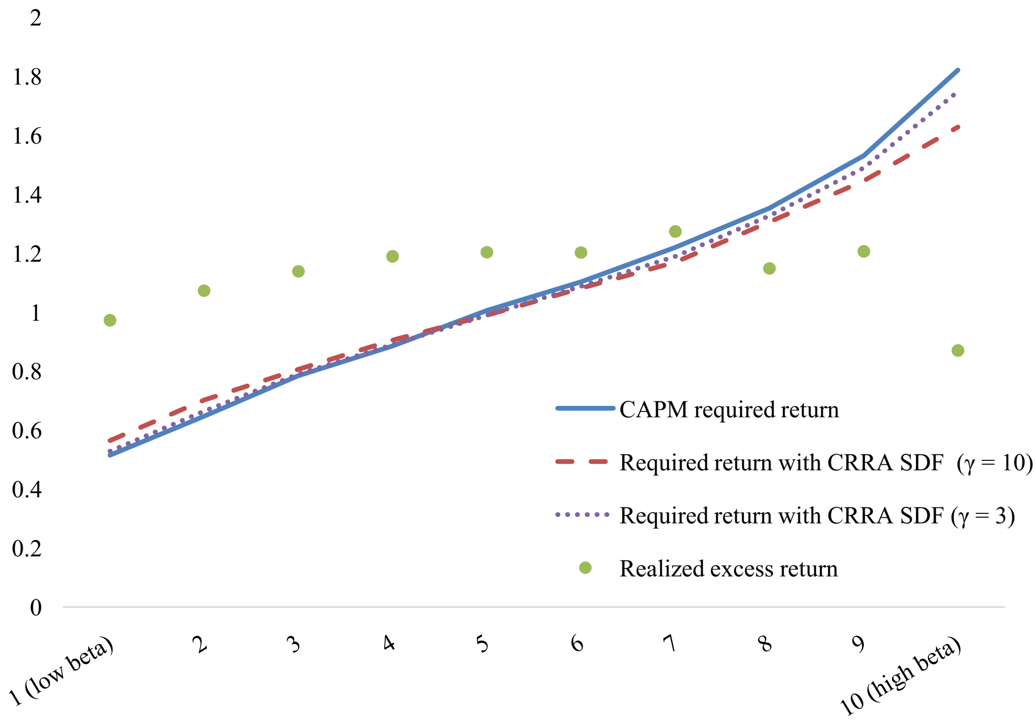

Fig. 2. Realized and required return for beta-sorted portfolios.
This figure shows the realized and required return to beta-sorted portfolios using three different asset pricing models. The green dots show the average realized excess returns for ten beta-sorted portfolios (normalized by dividing by the average market excess return). The solid blue line shows the portfolio's required returns based on the capital asset pricing model (again normalized by dividing by the required market excess return). The dashed red line and the dotted purple line show the required returns implied by a stochastic discount factor (SDF) for the constant relative risk aversion (CRRA) investor with risk aversion of $\gamma = 10$ and $\gamma = 3$ respectively, 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 break-points. Within each portfolio, stocks are value-weighted based on the market value at the end of the previous month. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

a CRRA investor with risk aversion of 10.[14] 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 to buy the low-beta portfolio, whereas the CAPM investor requires 0.51 times the market return. 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, skew risk of this form is too small to explain the low-risk effect.

5.3.3. Time-varying betas

Cederburg and O'Doherty (2016) find that the low-risk effect is explained by time-varying conditional betas. This could 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. Time-varying betas could matter anyway for two reasons. (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 can 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 et al. (2018) vary the methodology of Cederburg and O'Doherty slightly, and they find that controlling for conditional betas cannot explain the low-risk effect (Table A2). In fact, in Liu et al.'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

[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, $-\mathrm{cov}[r_t^i, (1+r_t^m)^{-\gamma}]$.

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 because 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% 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 (2018) explicitly test the effect of time-varying betas of the BAB factor using a noninstrumental approach, finding that time variation in betas can explain only around 20% of BAB's CAPM alpha.

6. Horse race

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 indicates that the competing explanations share an element related to volatility and 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 horse race.

6.1. Horse race based on published factors

We first consider a horse race between the various factors constructed as in the papers where they were first considered (as we have also done in the previous analysis). Table 9 shows the results of regressing each systematic and 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 9 reports our findings for US factors. The BAB factor in the US has a positive and significant alpha (t-statistic of 3.0) when controlling for LMAX and IVOL, the five Fama–French factors, and REV. Further, BAC has an even more significant alpha when controlling for these factors BAC has an alpha of 0.5% 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 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 9 that BAV is not robust to controlling for LMAX, the five Fama–French factors, and REV. This finding is not surprising because 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. BAV has significant excess returns, one-factor, and three-factor alpha, so its alpha turns insignificant only when we control for all other factors, which could simply reflect that the collection of right-hand-side variables already captures effects of leverage constraints (as discussed above).

We next turn our attention to the idiosyncratic factors in Table 9. LMAX and IVOL have insignificant alphas in the regressions in which 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 could 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 9 shows the same factor regressions in the global sample. 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 the methodologies differ across factors. BAB (and, likewise, BAC and BAV) are rank-weighted, and 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 10 shows that LMAX and IVOL have much faster turnover than BAB, BAC, and BAV. LMAX and IVOL have a monthly turnover of about \$2. Said differently, an idiosyncratic volatility factor that goes long \$1 and shorts \$1 has an annual turnover of about $12 \times \$2 = \$24$. The Fama–French and BAB-type factors have about six times lower turnover (e.g., BAC has a monthly turnover of \$0.35). 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 could 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 behavioral investors could find keeping track of such transient properties more difficult. 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 instead of the

Table 9
Horse race: 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 US 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, small minus big), value (HML, high minus low), profitability (RMW, robust minus weak), investment (CMA, conservative minus agressive), and short-term reversal (REV). *t*-statistics are shown in parentheses below the coefficient estimates, and 5% statistical significance is indicated in bold. The Sharpe ratio (SR) and information ratio (IR) are annualized.

	BAB	BAC	BAV	LMAX	SMAX	IVOL
Panel A: U.S. sample (1963–2015)						
Alpha	**0.31**	**0.52**	**−0.19**	0.05	**0.18**	0.07
	(3.04)	(4.79)	(−1.99)	(0.63)	(2.68)	(0.91)
MKT	**0.36**	**0.07**	**0.46**	**−0.42**	**−0.10**	**−0.38**
	(11.5)	(2.3)	(15.8)	(−22.2)	(−6.4)	(−18.7)
SMB	**0.35**	**0.66**	−0.02	**−0.41**	−0.04	**−0.53**
	(8.2)	(15.0)	(−0.4)	(−15.7)	(−1.9)	(−19.2)
HML	**0.13**	0.10	**0.14**	**0.10**	**−0.07**	**0.12**
	(2.6)	(2.0)	(3.0)	(2.7)	(−2.1)	(2.9)
RMW	0.07	**−0.12**	**0.35**	**0.39**	0.05	**0.55**
	(1.2)	(−2.0)	(6.2)	(9.9)	(1.6)	(13.0)
CMA	0.03	−0.05	−0.01	**0.35**	**0.10**	**0.37**
	(0.4)	(−0.6)	(−0.1)	(6.3)	(2.2)	(6.3)
REV	**−0.21**	**−0.12**	**−0.17**	**0.21**	**0.37**	0.01
	(−5.8)	(−3.2)	(−5.0)	(8.6)	(17.9)	(0.5)
BAB				**0.39**	**0.15**	**0.28**
				(15.5)	(7.0)	(10.4)
LMAX	**0.79**	**0.75**	**0.35**			
	(10.7)	(9.6)	(5.1)			
IVOL	−0.11	**−0.48**	**0.61**			
	(−1.4)	(−6.1)	(8.6)			
SR	0.90	0.85	0.31	0.34	0.78	0.22
IR	0.45	0.71	−0.30	0.09	0.40	0.14
R^2	0.44	0.42	0.74	0.81	0.39	0.81
Number of observations	630	630	630	630	630	630
Panel B: Global sample (1990–2015)						
	BAB	BAC	BAV	LMAX	SMAX	IVOL
Alpha	**0.25**	**0.40**	−0.18	−0.13	0.00	−0.11
	(2.37)	(3.73)	(−1.77)	(−1.56)	(0.06)	(−1.25)
MKT	**0.41**	**0.22**	**0.36**	**−0.43**	**−0.11**	**−0.34**
	(10.7)	(5.7)	(10.1)	(−18.8)	(−5.2)	(−13.5)
SMB	**0.70**	**0.74**	0.09	**−0.49**	−0.03	**−0.63**
	(11.7)	(12.3)	(1.6)	(−11.3)	(−0.8)	(−13.5)
HML	**0.17**	0.08	**0.19**	0.01	0.02	0.00
	(2.6)	(1.1)	(3.1)	(0.2)	(0.4)	(0.0)
RMW	**0.22**	0.15	0.06	**0.43**	0.09	**0.50**
	(2.3)	(1.6)	(0.7)	(6.3)	(1.4)	(6.8)
CMA	**−0.20**	−0.09	**−0.21**	**0.51**	0.10	**0.57**
	(−2.1)	(−1.0)	(−2.4)	(7.8)	(1.6)	(8.2)
REV	**−0.22**	**−0.11**	**−0.21**	**0.24**	**0.40**	**0.11**
	(−5.6)	(−2.6)	(−5.4)	(8.5)	(15.2)	(3.5)
BAB				**0.47**	**0.15**	**0.40**
				(13.5)	(4.5)	(10.5)
LMAX	**0.83**	**0.75**	**0.40**			
	(7.2)	(6.4)	(3.6)			
IVOL	−0.02	**−0.50**	**0.70**			
	(−0.2)	(−4.3)	(6.4)			
SR	0.97	0.94	0.36	0.34	0.41	0.35
IR	0.52	0.81	−0.39	−0.34	0.01	−0.27
R^2	0.63	0.46	0.80	0.88	0.50	0.85
Number of observations	306	306	306	306	306	306

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 one-year look-back period.

As can be seen in Table 10, the idiosyncratic risk factors with one-year look-back 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 10
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. For betting against correlation (BAC) and betting against volatility (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. US sorts are based on NYSE break-points. 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 low maximum return (LMAX), scaled maximum return (SMAX), and low idiosyncratic volatility (IVOL). Panel A reports the results from the US 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 US securities, the size break-point is the median NYSE market equity. For international securities, the size break-point is the 80th percentile by country. The MAX (SMAX, IVOL) break-points are the 30th and 70th percentile. We use unconditional sorts in the US 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 break-points. 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 et al. (2006). The US sample is 1926 to 2015. FF refers to Fama and French.

	Portfolio										
Method	HML FF: june update	BAB FF: june update	BAB FF: monthly	BAB Rank weights	BAC Rank weights	BAV Rank weights	LMAX FF: monthly	SMAX FF: monthly	IVOL FF: monthly	LMAX(1Y) FF: monthly	SMAX(1Y) 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	1–5 years	1–5 years	1–5 years	1–5 years	1–5 years	1 month	1–12 months	1 month	1 year	1 year

Table 11 shows the return to LMAX(1Y) and SMAX(1Y). 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, Fig. 3 plots the cumulative alpha in event time, relative to the portfolio formation period. Panel A plots the three-factor alphas and Panel B plots five-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 three-factor alphas of LMAX and LMAX(1Y) gradually rise over the next 12 months, although these curves flatten out. The cumulative alpha of SMAX is striking. It flattens out after one 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 Fig. 3 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 three-factor or five-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 one-year lookback now earn alpha only 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). LMAX seems to pick 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 horse race in which all factors are constructed based on the Fama–French methodology. 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 take an equal-weighted average of these five factors.

The results are reported in Table 12. 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

Table 11
Maximum return (MAX) factors based on yearly book-back periods.
This table shows regression results for monthly returns to low maximum return (LMAX) and scaled maximum return (SMAX) factors that are produced based on yearly estimates of MAX. Panel A reports the results from the long US sample and Panel B reports the results from the global sample. LMAX(1Y) [SMAX(1Y)] is constructed as the intersection of six value-weighted portfolios formed on size and MAX(1Y) [SMAX(1Y)]. For US securities, the size break-point is the median NYSE market equity. For international securities, the size break-point is the 80th percentile by country. The MAX(1Y) [SMAX(1Y)] break-points are the 30th and 70th percentile. We use unconditional sorts in the US and conditional sorts in the international sample (first we sort on size and then LMAX(1Y) [SMAX(1Y)]). Firms are assigned to one of six portfolios based on these break-points. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. LMAX(1Y) [SMAX(1Y)] is then the average return to the two low MAX(1Y) [SMAX(1Y)] portfolios minus the average return to the two high MAX(1Y) [SMAX(1Y)] 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(1Y) is the sum of the 20 highest returns over the previous year. SMAX(1Y) is the MAX(1Y) 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 (small minus big), HML (high minus low), RMW (robust minus weak), CMA (conservative minus aggressive), REV (short term reversal), and BAB (betting against beta) 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 parentheses below the coefficient estimates, and 5% statistical significance is indicated in bold. The Sharpe ratio (SR) and information ratio (IR) are annualized.

	LMAX(1Y)			SMAX(1Y)		
Panel A: U.S. sample (1963–2015)						
Alpha	**0.40**	0.08	−0.11	−0.13	**−0.25**	**−0.23**
	(3.71)	(0.85)	(−1.30)	(−1.64)	(−3.53)	(−3.21)
MKT	**−0.50**	**−0.43**	**−0.47**	0.00	**−0.05**	**−0.04**
	(−19.6)	(−17.6)	(−21.9)	(0.1)	(−2.6)	(−2.4)
SMB	**−0.67**	**−0.54**	**−0.59**	**−0.23**	**−0.21**	**−0.21**
	(−18.8)	(−16.0)	(−20.0)	(−9.0)	(−8.8)	(−8.5)
HML	**0.36**	**0.11**	0.00	**0.16**	**0.16**	**0.18**
	(9.3)	(2.3)	(−0.0)	(5.7)	(4.8)	(5.1)
RMW		**0.61**	**0.42**		**0.17**	**0.19**
		(12.3)	(9.4)		(4.8)	(5.1)
CMA		**0.52**	**0.37**		−0.07	−0.05
		(7.3)	(5.9)		(−1.3)	(−1.0)
REV		0.04	**0.06**		**0.25**	**0.25**
		(1.3)	(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	0.52	0.13	−0.19	−0.23	−0.52	−0.48
R^2	0.68	0.75	0.81	0.18	0.34	0.34
Number of observations	630	630	630	630	630	630
Panel B: Global sample (1990–2015)						
Alpha	**0.39**	−0.11	**−0.24**	−0.18	**−0.28**	**−0.26**
	(2.90)	(−0.92)	(−2.63)	(−1.95)	(−3.30)	(−3.11)
MKT	**−0.65**	**−0.41**	**−0.46**	0.00	−0.04	−0.03
	(−21.3)	(−12.8)	(−18.3)	(−0.2)	(−1.7)	(−1.4)
SMB	**−0.58**	**−0.32**	**−0.59**	**−0.29**	**−0.25**	**−0.22**
	(−9.2)	(−5.7)	(−12.4)	(−6.6)	(−6.2)	(−4.9)
HML	**0.48**	0.02	**−0.14**	**0.22**	**0.22**	**0.24**
	(8.2)	(0.3)	(−2.4)	(5.5)	(4.3)	(4.6)
RMW		**0.93**	**0.43**		**0.21**	**0.27**
		(10.8)	(5.7)		(3.4)	(3.8)
CMA		**0.72**	**0.54**		−0.06	−0.04
		(7.8)	(7.5)		(−1.0)	(−0.6)
REV		0.03	**0.06**		**0.29**	**0.28**
		(0.8)	(2.0)		(9.9)	(9.8)
BAB			**0.55**			−0.06
			(14.1)			(−1.8)
SR	0.20	0.20	0.20	−0.25	−0.25	−0.25
IR	0.59	−0.20	−0.58	−0.39	−0.72	−0.68
R^2	0.68	0.79	0.87	0.22	0.43	0.43
Number of observations	306	306	306	306	306	306

Table 12
Horse race: factors based on Fama–French methodology.
This table reports regression results of horse races in which 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 (betting against beta), BAC (betting against correlation), BAV (betting against volatility), LMAX (low maximum return), SMAX (scaled maximum return), SMAX(1Y) (one-year look-back SMAX), and IVOL (low idiosyncratic volatility). 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 US securities, the size break-point is the median NYSE market equity. For international securities, the size break-point is the 80th percentile by country. The beta break-points are the 30th and 70th percentile. We use unconditional sorts in the US 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 capital asset pricing model alpha. For BAC and BAV, we create a factor within each volatility (correlation) quintile, and the BAC (BAV) factor is then the average 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 et al. (2006). Returns and alphas are in monthly percent, *t*-statistics are shown in parentheses below the coefficient estimates, and 5% statistical significance is indicated in bold. The Sharpe ratio (SR) and information ratio (IR) are annualized.

All FF-weights	BAB	BAB	BAC	BAC	BAV	BAV	LMAX	SMAX	SMAX(1Y)	IVOL
Panel A: U.S. sample (1963–2015)										
Alpha	**0.28**	**0.20**	**0.18**	0.14	**0.23**	**0.15**	0.06	**0.21**	**−0.25**	0.06
	(2.57)	(3.26)	(2.07)	(1.88)	(2.24)	(2.85)	(1.04)	(3.16)	(−3.41)	(0.90)
MKT	**−0.57**	**−0.18**	**−0.33**	**−0.16**	**−0.46**	**−0.09**	−0.03	−0.01	**−0.06**	**−0.05**
	(−21.1)	(−9.6)	(−15.7)	(−7.1)	(−18.4)	(−5.4)	(−1.7)	(−0.4)	(−2.6)	(−2.2)
SMB	**−0.37**	**0.12**	**0.13**	**0.34**	**−0.61**	**−0.14**	**−0.14**	0.03	**−0.22**	**−0.31**
	(−9.8)	(4.8)	(4.4)	(11.1)	(−17.8)	(−6.7)	(−6.5)	(1.1)	(−8.5)	(−12.8)
HML	**0.19**	**0.09**	0.04	0.00	**0.14**	0.05	**0.09**	−0.05	**0.17**	**0.09**
	(3.6)	(3.0)	(1.1)	(0.0)	(3.0)	(1.9)	(3.1)	(−1.7)	(4.9)	(2.9)
RMW	**0.40**	**−0.15**	0.05	**−0.19**	**0.49**	−0.04	**0.33**	0.07	**0.18**	**0.47**
	(7.3)	(−4.4)	(1.1)	(−4.5)	(9.7)	(−1.2)	(10.7)	(1.9)	(4.8)	(13.6)
CMA	**0.39**	−0.08	**0.14**	−0.06	**0.39**	−0.06	**0.25**	**0.11**	−0.06	**0.27**
	(5.0)	(−1.6)	(2.4)	(−1.1)	(5.4)	(−1.5)	(5.9)	(2.2)	(−1.1)	(5.6)
REV	−0.06	**−0.09**	**−0.09**	**−0.10**	0.02	−0.02	**0.22**	**0.37**	**0.25**	0.03
	(−1.6)	(−4.6)	(−3.3)	(−4.3)	(0.5)	(−1.1)	(11.9)	(17.7)	(10.8)	(1.3)
BAB							**0.62**	**0.14**	−0.03	**0.53**
							(28.8)	(5.9)	(−1.0)	(21.9)
LMAX(1Y)		**0.90**		**0.39**		**0.86**				
		(35.6)		(12.8)		(39.6)				
SR	0.11	0.11	0.09	0.09	0.10	0.10	0.34	0.78	−0.22	0.22
IR	0.38	0.48	0.30	0.28	0.33	0.42	0.15	0.47	−0.50	0.13
R^2	0.71	0.90	0.42	0.54	0.74	0.93	0.89	0.37	0.34	0.87
Number of observations	630	630	630	630	630	630	630	630	630	630
Panel B: Global sample (1990–2015)										
Alpha	−0.06	0.04	0.02	0.07	0.01	0.09	0.02	0.05	0.05	**−0.28**
	(−0.41)	(0.40)	(0.18)	(0.74)	(0.05)	(1.15)	(0.23)	(0.64)	(0.64)	(−3.34)
MKT	**−0.48**	**−0.13**	**−0.22**	−0.04	**−0.44**	**−0.13**	**−0.12**	−0.02	−0.02	**−0.06**
	(−12.7)	(−3.9)	(−7.7)	(−1.2)	(−13.5)	(−4.8)	(−5.0)	(−0.9)	(−0.9)	(−2.1)
SMB	−0.12	**0.15**	**0.26**	**0.40**	**−0.56**	**−0.32**	**−0.19**	0.06	0.06	**−0.26**
	(−1.9)	(3.3)	(5.3)	(9.0)	(−9.9)	(−8.1)	(−5.4)	(1.6)	(1.6)	(−6.3)
HML	−0.16	**−0.17**	**−0.20**	**−0.21**	−0.04	−0.06	**0.23**	0.09	0.09	**0.22**
	(−1.9)	(−3.1)	(−3.3)	(−4.0)	(−0.5)	(−1.2)	(5.3)	(1.9)	(1.9)	(4.2)
RMW	**0.83**	0.03	**0.41**	0.00	**0.63**	−0.08	**0.40**	0.10	0.10	**0.25**
	(8.2)	(0.3)	(5.5)	(0.1)	(7.2)	(−1.2)	(6.9)	(1.5)	(1.5)	(3.6)
CMA	**0.76**	0.15	**0.41**	0.10	**0.65**	0.10	**0.24**	0.03	0.03	−0.03
	(7.2)	(1.9)	(5.2)	(1.3)	(7.1)	(1.5)	(4.0)	(0.5)	(0.5)	(−0.4)
REV	−0.05	**−0.08**	**−0.13**	**−0.14**	0.00	−0.03	**0.24**	**0.40**	**0.40**	**0.28**
	(−1.0)	(−2.4)	(−3.7)	(−4.8)	(−0.0)	(−1.0)	(9.8)	(15.2)	(15.2)	(9.8)
BAB							**0.55**	**0.15**	**0.15**	−0.05
							(18.2)	(4.8)	(4.8)	(−1.3)
LMAX(1Y)		**0.86**		**0.44**		**0.76**				
		(18.9)		(10.0)		(20.1)				
SR	0.14	0.14	0.15	0.15	0.15	0.15	0.34	0.41	0.41	−0.25
IR	−0.09	0.09	0.04	0.16	0.01	0.25	0.05	0.14	0.14	−0.73
R^2	0.73	0.88	0.55	0.66	0.77	0.90	0.91	0.51	0.51	0.43
Number of observations	306	306	306	306	306	306	306	306	306	306

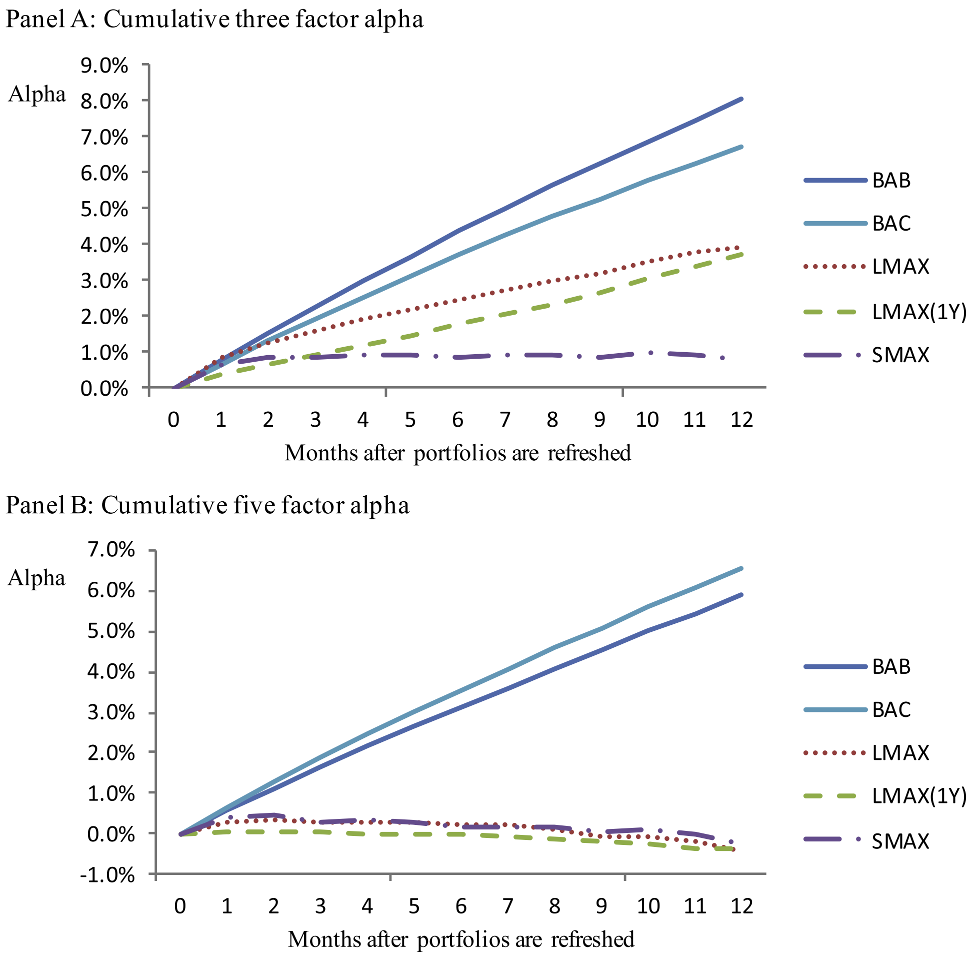

Fig. 3. Cumulative alpha for longer holding periods.
This figure shows cumulative alpha for trading strategies in event time. The event time is months after the characteristics were last refreshed. The strategies we consider are betting against beta (BAB), betting against correlation (BAC), LMAX, LMAX based on one-year lookback period LMAX(1Y), and scaled MAX (SMAX).

alpha of BAC becomes insignificant once also controlling for LMAX, but the alphas of BAB and BAV are robust to controlling for LMAX. Looking at idiosyncratic risk factors, SMAX is the only factor with significant alpha.

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

We next run a horse race in which all factors are rank-weighted. Because 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, similarly to Fama and French (1993), we 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

$$HML_{t+1}^{Rank} = 0.5HML_{t+1}^{Rank,small} + 0.5HML_{t+1}^{Rank,large}, \tag{13}$$

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 13 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 13 is that their alphas are robust to using rank-weighted factors on the right-hand side. The alphas for BAB and BAC remain 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 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 low or even negative alphas is that the rank-weighted right-hand-side factors are even more effective in explaining them.

Table 13
Horse race: rank-weighted factors.
This table reports regression results of horse races in which all factors are rank-weighted. The dependent variables are the monthly returns BAB (betting against beta), BAC (betting against correlation), BAV (betting against volatility), LMAX (low maximum return), SMAX (scaled maximum return), and IVOL (low idiosyncratic volatility). 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 break-point 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 capital asset pricing model 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 et al. (2006). Returns and alphas are in monthly percent, *t*-statistics are shown in parentheses below the coefficient estimates, and 5% statistical significance is indicated in bold. The Sharpe ratio (SR) and information ratio (IR) are annualized.

U.S. sample (1952–2015)	BAB	BAB	BAC	BAC	BAV	BAV	LMAX	LMAX	SMAX	SMAX	IVOL	IVOL
Alpha	**0.45**	**0.41**	**0.36**	**0.35**	0.18	0.07	0.18	−0.22	0.19	0.05	0.26	−0.06
	(4.63)	(4.69)	(4.24)	(4.16)	(1.28)	(1.22)	(0.83)	(−1.14)	(1.30)	(0.33)	(1.95)	(−0.52)
MKT	−0.01	0.00	−0.03	−0.02	**−0.08**	**−0.04**	−0.06	−0.05	−0.01	0.00	**−0.09**	**−0.08**
	(−0.3)	(0.2)	(−1.3)	(−1.2)	(−2.4)	(−3.0)	(−1.2)	(−1.2)	(−0.2)	(−0.2)	(−2.8)	(−3.0)
SMB	**0.09**	**0.06**	**0.21**	**0.20**	**−0.13**	**−0.25**	**0.19**	**0.11**	**0.26**	**0.23**	**−0.07**	**−0.14**
	(7.3)	(4.7)	(19.0)	(17.7)	(−7.4)	(−30.6)	(7.0)	(4.2)	(13.7)	(12.0)	(−4.2)	(−9.0)
HML	**0.56**	**0.43**	**0.26**	**0.22**	**0.80**	**0.39**	**0.69**	0.19	**0.16**	−0.02	**0.58**	**0.18**
	(11.1)	(9.1)	(5.9)	(5.0)	(11.0)	(12.1)	(6.3)	(1.8)	(2.1)	(−0.2)	(8.3)	(2.8)
RMW	**0.46**	**0.19**	−0.07	**−0.15**	**1.22**	**0.36**	**1.46**	**1.05**	**0.60**	**0.46**	**1.26**	**0.93**
	(10.2)	(4.0)	(−1.9)	(−3.3)	(19.0)	(11.5)	(14.9)	(11.0)	(8.9)	(6.4)	(20.1)	(16.3)
CMA	−0.01	0.05	−0.02	0.00	0.07	**0.25**	−0.31	**−0.30**	**−0.41**	**−0.40**	0.13	0.13
	(−0.1)	(0.7)	(−0.3)	(−0.0)	(0.7)	(5.5)	(−1.9)	(−2.0)	(−3.7)	(−3.7)	(1.2)	(1.5)
REV	**−0.07**	**−0.10**	**−0.06**	**−0.07**	−0.05	**−0.16**	**0.18**	**0.24**	**0.35**	**0.37**	**−0.10**	**−0.05**
	(−3.1)	(−5.0)	(−3.0)	(−3.5)	(−1.7)	(−11.5)	(3.8)	(5.5)	(10.7)	(11.5)	(−3.3)	(−2.0)
BAB								**0.90**		**0.32**		**0.72**
								(12.3)		(5.9)		(16.8)
LMAX		**0.19**		**0.05**		**0.59**						
		(12.3)		(3.5)		(57.0)						
SR	0.85	0.85	0.72	0.72	0.32	0.32	0.53	0.53	0.70	0.70	0.36	0.36
IR	0.67	0.68	0.62	0.61	0.19	0.18	0.12	−0.17	0.19	0.05	0.29	−0.08
R^2	0.44	0.54	0.41	0.42	0.70	0.94	0.42	0.51	0.40	0.42	0.67	0.76
Number of observations	762	762	762	762	762	762	762	762	762	762	761	761

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 for which leverage constraints are in principle directly observable and changeable, e.g., for many pension funds and mutual funds. Likewise, if professional asset managers 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 US 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 horse races between the low-risk factors, 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 because the idiosyncratic risk factors derive much of their alphas from a short-term effect.

In conclusion, our results suggest that leverage constraints, mispricing, and lottery demand all play a role in 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.

References

Adrian, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross–section of stock returns. J. Financ. 69 (6), 2557–2596.
Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. J. Financ. 61 (1), 259–299.
Ang, A, Hodrick, Robert J., Xing, Yuhang, Zhang, Xiaoyan, 2009. High idiosyncratic volatility and low returns: international and further US evidence. J. Financ. Econ. 91 (1), 1–23.
Asness, C., Frazzini, A., 2013. The devil in HML's details. J. Portf. Manag. 39, 49–68.
Asness, C.S., Frazzini, A., Pedersen, L.H., 2014. Low-risk investing without industry bets. Financ. Anal. J. 70 (4), 24–41.
Asness, C., Frazzini, A., Pedersen, L.H., 2019. Quality minus junk. Rev. Account. Stud. 24 (1), 34–112.
Baker, M., Bradley, B., Wurgler, J., 2011. Benchmarks as limits to arbitrage: understanding the low volatility anomaly. Financ. Anal. J. 67 (1), 40–54.
Baker, M., Hoyer, M.F., Wurgler, J., 2020. The risk anomaly tradeoff of leverage. J. Financ. Quant. Anal. Forthcoming.
Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Financ. 61 (4), 1645–1680.
Baker, M., Wurgler, J., 2015. Do strict capital requirements raise the cost of Capital? Bank regulation and the low risk anomaly. Am. Econ. Rev. 105 (5), 315–320.
Bali, T.G, Brown, S., Murray, S., Tang, Y., 2017. A lottery demand-based explanation of the beta anomaly. J. Financ. Quant. Anal. 52 (6), 2369–2397.
Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. J. Financ. Econ. 99 (2), 427–446.
Barberis, N., Huang, M., 2008. Stocks as lotteries: the implications of probability weighting for security prices. Am. Econ. Rev. 98 (5), 2066–2100.
Black, F., 1972. Capital market equilibrium with restricted borrowing. J. Bus. 45, 444–455.
Black, F., Jensen, M.C., Scholes, M., 1972. The capital asset pricing model: some empirical tests. In: Jensen, M.C. (Ed.), Studies in the Theory of Capital Markets. Praeger, New York, pp. 79–121.
Boguth, O., Simutin, M., 2018. Funding constraints and asset prices: insights from mutual fund risk taking. J. Financ. Econ. 127, 325–341.
Boyer, B., Mitton, T., Vorkink, K., 2009. Expected idiosyncratic skewness. Rev. Financ. Stud. 23 (1), 169–202.
Brennan, M.J., 1993. Agency and Asset pricing. University of California, Los Angeles, CA Unpublished Working Paper.
Brunnermeier, M.K., Gollier, C., Parker, J.A., 2007. Optimal beliefs, asset prices, and the preference for skewed returns. Am. Econ. Rev. 97 (2), 159–165.
Cederburg, S., O'Doherty, M.S., 2016. Does it pay to bet against beta? On the conditional performance of the beta anomaly. J. Financ. 71 (2), 737–774.
Cohen, R.B., Polk, C., Vuolteenaho, T., 2005. Money illusion in the stock market: the Modigliani–Cohn hypothesis. Q. J. Econ. 120 (2), 639–668.
Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Financ. 47 (2), 427–465.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33, 3–56.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116, 1–22.
Fama, E.F., French, K.R., 2016. Dissecting anomalies with a five-factor model. Rev. Financ. Stud. 29 (1), 69–103.
Frazzini, A., Pedersen, L.H., 2011. Embedded Leverage. AQR Capital Management and New York University, Greenwich, CT and New York, NY Unpublished Working Paper.
Frazzini, A., Pedersen, L.H., 2014. Betting against beta. J. Financ. Econ. 111, 1–25.
Gormsen, N.J., Jensen, C.S., 2018. Conditional Risk. University of Chicago and Bocconi University, Chicago, IL, USA and Milano, Italy Unpublished Working Paper.
Hong, H., Sraer, D.A., 2016. Speculative betas. J. Financ. 71 (5), 2095–2144.
Hu, G.X., Pan, J., Wang, J., 2013. Noise as information for illiquidity. J. Financ. 68 (6), 2341–2382.
Jylhä, P., 2018. Margin requirements and the security market line. J. Financ. 73 (3), 1281–1321.
Kraus, A., Litzenberger, R.H., 1976. Skewness preference and the valuation of risk assets. J. Financ. 31 (4), 1085–1100.
Lewellen, J., Nagel, S., 2006. The conditional CAPM does not explain asset-pricing anomalies. J. Financ. Econ. 82 (2), 289–314.
Liu, J., Stambaugh, R.F., Yuan, Y., 2018. Absolving beta of volatility's effects. J. Financ. Econ. 128, 1–15.
Malkhozov, A., Mueller, P., Vedolin, A., Venter, G., 2016. International Illiquidity. Social Science Research Network. Unpublished Working Paper.
Modigliani, F., Cohn, R., 1979. Inflation, rational valuation, and the market. Financ. Anal. J. 35 (3), 24–44.
Novy-Marx, R., 2014. Understanding Defensive equity. University of Rochester, Rochester, NY. Unpublished NBER Working Paper.
Schneider, P., Wagner, C., Zechner, J., 2016. Low Risk Anomalies?. University of Frankfurt, Centre for Financial Studies, Frankfurt am Main, Germany, p. 550 Unpublished Working Paper.
Stambaugh, R.F., Yu, J., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. J. Financ. 70 (5), 1903–1948.
Vasicek, O.A., 1973. A note on using cross-sectional information in Bayesian estimation on security betas. J. Financ. 28 (5), 1233–1239.