Low Risk Anomalies? *

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February 2016

Abstract

This paper shows theoretically and empirically that beta- and volatility-based low risk anomalies are driven by return skewness. The empirical patterns concisely match the predictions of our model which generates skewness of stock returns via default risk. With increasing downside risk, the standard capital asset pricing model increasingly overestimates required equity returns relative to firms' true (skew-adjusted) market risk. Empirically, the profitability of betting against beta/volatility increases with firms' downside risk. Our results suggest that the returns to betting against beta/volatility do not necessarily pose asset pricing puzzles but rather that such strategies collect premia that compensate for skew risk.

Keywords: Low risk anomaly, skewness, credit risk, risk premia, equity options.

*This paper received the 2015 Jack Treynor Prize sponsored by the Q-Group (The Institute for Quantitative Research in Finance). We are grateful to Kevin Aretz, Turan Bali, Michael Brennan, John Campbell, Mikhail Chernov, Peter Christoffersen, Andrea Gamba, Christopher Hennessy, Christopher Hrdlicka, Leonid Kogan, Miriam Marra, Ian Martin, Lasse Pedersen, Paulo Rodrigues, Ivan Shaliastovich, Christian Schlag, Rossen Valkanov, Pietro Veronesi, Arne Westerkamp, Paul Whelan, Liuren Wu, and participants at the 10th Annual Conference on Advances in the Analysis of Hedge Fund Strategies (London), the IFSID Conference on Derivatives (Montreal), the SAFE Asset Pricing Workshop (Frankfurt), as well as seminar participants at Cass Business School, Copenhagen Business School, Hong Kong University of Science and Technology, Imperial College, Singapore Management University, Stockholm School of Economics, University of Geneva, University of Toronto (Rotman), Warwick Business School, and WU Vienna for helpful comments. This paper replaces an earlier draft entitled "The Cross-Section of Credit, Variance, and Skew Risk". Paul Schneider acknowledges support from the Swiss National Science Foundation grant "Trading Asset Pricing Models" and the Swiss Finance Association grant "Term Structures and Cross-Sections of Asset Risk Premia". Christian Wagner acknowledges support from the Center for Financial Frictions (FRIC), grant no. DNRF102. The authors alone are responsible for any errors and for the views expressed in the paper.

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1 Introduction

Empirical findings that low-beta stocks outperform high beta stocks and that (idiosyncratic) volatility negatively predicts equity returns have spurred a large literature on 'low risk anomalies' (e.g., Haugen and Heins, 1975; Ang et al., 2006; Baker et al., 2011; Frazzini and Pedersen, 2014). This paper shows that the returns to trading such anomalies may be rationalized when accounting for the skewness of equity returns, which standard measures of market risk and (idiosyncratic) volatility ignore.

To motivate our empirical analysis, we employ an asset pricing model that uses the market as systematic risk factor, that nests the standard Capital Asset Pricing Model (CAPM) as an approximation, but that also accounts for higher moments of the return distribution. To introduce a direct channel for higher-order equity return moments, we embed the credit risk model of Merton (1974) in our market model. In such a setting, default risk acts as a natural source of skewness in returns that affects the joint distribution of firms' equity and market returns. The higher a firm's credit risk, the more the CAPM overestimates the firm's market risk, because it ignores the impact of skewness on asset prices (e.g., Kraus and Litzenberger, 1976; Harvey and Siddique, 2000). As a consequence, subsequent equity returns may appear too low when benchmarked against the CAPM, whereas in fact they reflect the firm's true market risk. Given that the CAPM systematically misestimates expected equity returns, idiosyncratic volatility measured from CAPM pricing errors conveys return-relevant information as well.

Our empirical results strongly support the predictions derived from the model. We show that ex-ante skewness predicts the cross-section of equity returns and that conditioning on ex-ante skewness affects the prevalence of low risk anomalies. The profitability of betting-against-beta strategies increases with firms' downside risk, and the return differential of implementing such strategies among low skew compared to high skew firms is economically large. These patterns are consistent with the model-implied CAPM misestimation of market risk. Similarly, we find that the negative relation between equity returns and idiosyncratic volatility (computed from CAPM or Fama French three factor model residuals) as well as ex-ante variance is most pronounced among firms with most negative equity ex-ante skewness. All these findings suggest that low risk anomalies may not be as anomalous as they appear at first sight.

We establish our empirical results for a cross-section of around 5,000 US firms for the period from January 1996 to August 2014, covering all CRSP firms for which data on common stocks and equity options is available. Using equity options data, we compute ex-ante skewness from an options portfolio that takes long positions in out-of-the-money (OTM) call options and short positions in OTM puts. This measure becomes more negative, the more expensive put options are relative to call options, i.e. if investors are willing to pay high premia for protection against downside risk.

Our empirical analysis starts by showing that ex-ante skewness conveys information for the distribution of future equity returns. In skew-sorted decile portfolios, we find that ex-ante skew positively predicts both realized skewness and equity returns. Firms with high ex-ante skewness generate a monthly alpha (controlling for market, size, value, and momentum factors) of around 0.82%, whereas the alpha of low skew firms is −0.54% per month. Low skew firms face the most extreme downside risk and exhibit, as predicted by the model, less coskewness with the market compared to firms with high ex-ante skewness. These results are consistent with the notion of Kraus and Litzenberger (1976) that investors require lower (higher) returns on stocks that are less (more) systematically exposed to extreme market situations.

Having established that ex-ante skewness contains information for the future distribution of equity returns, we explore its relevance for understanding low risk anomalies. Guided by the predictions of our model, we independently sort firms into quintile portfolios using their ex-ante skew and into quintile portfolios using either their CAPM beta, idiosyncratic volatility, or ex-ante variance. Within each of the skew portfolios, we compute the returns to trading on low risk anomalies, such as a betting-against-beta strategy. We find that the returns to trading on low risk anomalies increase with firms' downside risk and that the difference of betting against beta/volatility among low skew minus high skew firms is statistically significant and economically large. The Fama-French-Carhart four factor model alphas range from 1.15% to 1.76% per month and the performance is not driven by specific sample periods, but delivers steady returns over time.

Our results also provide new insights for the distress puzzle, a credit risk-related low risk anomaly, defined as the lack of a positive relation between distress risk and risk-adjusted equity returns (e.g., Campbell et al., 2008). Using data on firms' leverage, a key driver of default risk and skewness in our model, we find that the returns of leverage-sorted portfolios resemble the distress puzzle: buying high leverage firms and selling low leverage stocks generates negative alphas. Accounting for skewness, these alphas become much closer to zero and mostly insignificant.

Essentially, our theoretical and empirical results imply that empirical patterns labeled as low risk anomalies may not necessarily pose asset pricing puzzles. Taking the role of skewness into account, our findings suggest that the CAPM beta may not be a sufficient metric to judge a firm's market risk, and that equity returns - reflecting the firm's true market risk - may appear anomalous when benchmarked against the CAPM. These arguments also provide an understanding for the seemingly anomalous relations of (idiosyncratic) volatility to stock returns and credit risk to equity returns. Our results provide strong evidence that all these empirical patterns, which haven been established as mostly unrelated asset pricing puzzles in the literature, can be directly connected to skewness.

Various robustness checks confirm our findings and corroborate our conclusions. For instance, repeating the empirical analysis using the return-based coskewness measure of Harvey and Siddique (2000) also produces results consistent with our model, albeit statistically less significant compared to using option-implied estimates of ex-ante skewness. Additionally, we show that ex-ante skewness matters for low risk anomalies beyond lottery characteristics of stocks. Other checks verify that our results are robust to variations in the portfolio setup, return-weighting schemes, and time lags between the generation of option-implied signals and portfolio formation.

Related Literature. While the capital asset pricing model (CAPM, see Sharpe, 1964; Lintner, 1965; Mossin, 1966) postulates a positive relation between risk and return, there is a large body of research documenting that the empirical relation is flatter than implied by the CAPM or even negative. Early studies providing such evidence and attempting to explain the empirical failure of the CAPM include Brennan (1971), Black (1972), Black et al. (1972), and Haugen and Heins (1975). Recent research confirms these puzzling patterns and follows different approaches to provide insights on the anomalies. Ang et al. (2006, 2009) show that (idiosyncratic) volatility negatively predicts equity returns and that stocks with high sensitivities to aggregate volatility risk earn low returns. While Fu (2009) finds that the sign of the relation between idiosyncratic risk and returns depends on the specific risk measure employed, other papers argue that a negative relation can be understood when accounting for leverage (e.g. Johnson, 2004) or differences in beliefs and short-selling constraints (e.g. Boehme et al., 2009). Campbell et al. (2015) show that the low returns of stocks with high sensitivities to aggregate volatility risk are consistent with the intertemporal CAPM (Campbell, 1993) that allows for stochastic volatility.

To rationalize the profitability of betting against beta (BaB) strategies, Frazzini and Pedersen (2014) build on the idea of Black (1972) that restrictions to borrowing affect the shape of the security market line (SML). They present a model where leverage constrained investors bid up high-beta assets which in turn generate low risk-adjusted returns. Jylha (2015) provides further evidence for the role of leverage constraints by showing that the SML-slope is connected to margin requirements. Baker et al. (2011) argue that institutional investors' mandate to beat a fixed benchmark discourages arbitrage activity and thereby contributes to the anomaly. Hong and Sraer (2014) present a model with short-sale constrained investors in which high beta assets are more prone to speculative overpricing because they are more sensitive to macro-disagreement. Bali et al. (2011) find that accounting for the lottery characteristics of stocks reverses the relation between idiosyncratic volatility and equity returns, and Bali et al. (2015a) argue that the BaB anomaly is consistent with investors' preference for lottery stocks. Other papers study the properties of BaB returns, for instance, Baker et al. (2014) decompose these returns into micro and macro components. Huang et al. (2015) find that BaB activity itself affects the profitability of the strategy. Moreover, recent papers take the low risk anomaly as given and discuss consequences for capital structure theory; see Baker and Wurgler (2015b) for a tradeoff theory related to the low risk anomaly and Baker and Wurgler (2015a) for a more specific application of this idea to banks.

This paper takes a different approach by directly linking low risk anomalies to return skewness. Specifically, we build on the insight of Rubinstein (1973) and Kraus and Litzenberger (1976) that the empirical failure of the CAPM may be due to ignoring the effect of skewness on asset prices. Friend and Westerfield (1980) also find that coskewness with the market entails information for stock returns beyond covariance, Sears and Wei (1985) discuss the interaction of skewness and the market risk premium in asset pricing tests, and Harvey and Siddique (2000) show that conditional skewness helps explain the cross-section of equity returns.[1] With the widespread availability of equity options data, recent papers explore the relation of option-implied ex-ante skewness on subsequent equity returns but provide mixed evidence (e.g. Bali and Hovakimian, 2009; Xing et al., 2010; Rehman and Vilkov, 2012; Bali and Murray, 2013; Conrad et al., 2013), with differences in results driven by differences in skew-measure construction.[2] Bali et al. (2015b) provide complementary evidence by showing that ex-ante skewness is positively related to ex-ante stock returns estimated from analyst price targets. Other recent papers suggesting that skewness matters for the cross-section of equity returns are Amaya et al. (2015), who find a negative relation between realized skewness and subsequent equity returns, and Chang et al. (2013), who show that stocks that are most sensitive to changes in the market's ex-ante skewness, exhibit lowest returns. Buss and Vilkov (2012) apply the measure of Chang et al. (2013) to individual stocks, but do not find a pronounced relation to equity returns, whereas they do find that betas constructed from option-implied correlations exhibit a positive relation to subsequent stock returns. Our empirical results contribute to these previous findings by showing that accounting for skewness adds to our understanding of low risk anomalies associated with CAPM beta and measures of (idiosyncratic) volatility.

The remainder of this paper is organized as follows. Section 2 presents the theoretical framework that guides our empirical analysis. We describe the data and construction of variables in Section 3 and present the empirical results in Section 4. Section 5 discusses additional results and robustness checks. Section 6 concludes.

[1]Our approach, thus, builds on the idea that firms' skewness matters for asset prices through their coskewness component. This is conceptually very different from work that studies how idiosyncratic skewness can be priced in stock returns, such as Brunnermeier et al. (2007), Mitton and Vorkink (2007), Barberis and Huang (2008), and Boyer et al. (2009).

[2]For instance, Rehman and Vilkov (2012) and Conrad et al. (2013), both, use the ex-ante skew measure of Bakshi et al. (2003) but find a positive and negative relation to subsequent returns, respectively. Apparently, this difference in results stems from Rehman and Vilkov (2012) measuring ex-ante skew from the latest option-data only whereas Conrad et al. (2013) compute ex-ante skew measures for every day over the past quarter and then take the average, thereby smoothing out recent changes in skewness. In preceding work, Bali and Hovakimian (2009) show that the spread between near-the-money call and put option implied volatility positively predicts stock returns. Similarly, Xing et al. (2010) find that stocks with steep implied volatility smirks, defined as the difference between OTM put minus ATM call implied volatility, underperform stocks with less pronounced smirks. Bali and Murray (2013) construct a skewness asset as a combination of positions in equity options and the underlying stock and and find that its returns are negatively related to the option-implied skewness measure of Bakshi et al. (2003) .

2 Theoretical Framework

In this Section, we present the theory to guide our analysis of low risk anomalies, such as the finding that high CAPM beta stocks underperform relative to low beta stocks. Kraus and Litzenberger (1976) are the first to note that the lack of empirical support for the CAPM may be due to the model ignoring the effect of skewness on asset prices. Harvey and Siddique (2000) strengthen these results by showing that conditional skewness helps to explain the cross-section of equity returns. Therefore, skewness appears to be a plausible candidate to provide insights for beta- and volatility-based low risk anomalies that receive considerable attention in the recent literature (e.g., Ang et al., 2006; Frazzini and Pedersen, 2014).

We present an asset pricing model that uses the market as systematic risk factor, that nests the standard CAPM as a first-order approximation , but also accounts for higher moments of the return distribution (in the spirit of Harvey and Siddique, 2000). Within this framework, the effect of skewness on asset prices arises endogenously from incorporating the credit risk model of Merton (1974). Corporate credit risk acts as a natural source of skewness in returns, and we show that the CAPM is prone to overestimating the market risk and expected returns of high beta firms. The skew-implications for low risk anomalies remain unchanged when we incorporate additional drivers of skewness by allowing the asset process to exhibit jumps or stochastic volatility.

2.1 Market model

To account for the effect of skewness on asset prices, we draw on the work of Kraus and Litzenberger (1976), Harvey and Siddique (2000), and Schneider (2015). Kraus and Litzenberger (1976) are the first to propose a three moment CAPM to account for skew preferences in asset pricing. Harvey and Siddique (2000) provide a conditional version of their skew-aware CAPM. More specifically, they assume that the stochastic discount factor (or pricing kernel) is quadratic in the market return and show that the expected stock return is a function of the market excess returns and the squared market excess returns, with exposures on these factors being functions of market variance, the stock's (co)variance, and its (co)skewness. Schneider (2015) interprets these results as a truncated polynomial projection of the true, unknown pricing kernel on the market return and shows that to first- and second-order this framework corresponds to the standard and the skew-aware CAPM, respectively. The attractive feature of his framework is that it allows us to concisely track how and why the CAPM beta as a measure of market risk deviates from the 'skew-adjusted' beta and the 'true beta' that takes all higher moments into account.

To see how higher moments such as skewness matter for asset pricing, consider a representative power-utility investor who is exposed to stochastic volatility. We model the dynamics of the forward market price $M_{t,T}$, contracted at time t for delivery at T, as [3]

$$\begin{aligned} \frac{dM_{t,T}}{M_{t,T}} &= \eta_t\, dt + \kappa_t\, (\xi dW_t^{1\mathbb{P}} + \sqrt{1-\xi^2} dW_t^{2\mathbb{P}}), \\ d\kappa_t^2 &= (\nu_0 + \nu_1 \kappa_t^2)dt + \kappa_t \vartheta dW_t^{1\mathbb{P}}. \end{aligned} \tag{1}$$

With γ denoting the coefficient of constant relative risk aversion, $\eta_t = \gamma\kappa_t^2$ is the instantaneous market return in excess of the risk-free rate and κ_t is the associated market volatility. Campbell et al. (2015) develop an empirically successful asset pricing model with stochastic volatility in a similar way.[4] We define the (discrete) market excess return $R := \frac{M_{T,T}}{M_{0,T}} - 1$, where we suppress time subscripts here and subsequently for notational convenience, and set $M_{0,T} = 1$. Given the agent's local risk aversion γ, we obtain the forward pricing kernel ($\mathcal{M}$) as

$$\mathcal{M} := \frac{(R+1)^{-\gamma}}{e^{1/2(\gamma-\gamma^2)\int_0^T \kappa_s^2 ds}}. \tag{2}$$

Since the pricing kernel also depends on integrated variance it may be preferable to work with its expectation conditional on R,

$$\mathcal{M}(R) := \mathbb{E}^{\mathbb{P}}\left[\mathcal{M} \mid R\right]. \tag{3}$$

Schneider (2015) shows that a linear CAPM-type pricing kernel arises when approximating

[3] We choose to specify the dynamics of the forward price (rather than the spot price) because this naturally accounts for interest rates and ensures that the forward price is a martingale under the forward measure ($\mathbb{Q}_T$) with the T-period zero coupon bond as numeraire.

[4] The less realistic but more parsimonious case of modeling the market by a geometric Brownian motion only leads to qualitatively the same asset pricing implications as the stochastic volatility dynamics in Equation (1). In other words, higher moments of the return distribution matter for asset prices even if the market does not exhibit skewness; this point is also stressed by Kraus and Litzenberger (1976).

Equation (3) to first-order,[5]

$$\mathcal{M}_1(R) = a_1 + b_1 R, \tag{4}$$

where the coefficients a_1 and b_1 are functions of γ, T, and the parameters of the stochastic market variance process. Typical values entail $b_1 < 0$, reflecting the agent's relative risk aversion, consistent with decreasing marginal utility.

The second-order approximation to $\mathcal{M}(R)$ is quadratic in the market return and matches the pricing kernel specification of Harvey and Siddique (2000),

$$\mathcal{M}_2(R) = a_2 + b_2 R + c_2 R^2. \tag{5}$$

For $\gamma > 0$, we typically have that $b_2 < 0$ and $c_2 > 0$, which is consistent with non-increasing absolute risk aversion (because b_2 is proportional to U'' and c_2 is proportional to U'''). As discussed by Harvey and Siddique (2000), non-increasing absolute risk aversion can be related to prudence and disappointment aversion, which, in turn is consistent with the main result of Kraus and Litzenberger (1976) that investors accept lower (demand higher) expected returns on assets with positive (negative) skewness.

In the absence of arbitrage, the stochastic discount factor prices all risky asset payoffs in the economy. The expected return on asset i, $\mathbb{E}_0^{\mathbb{P}}[R_i]$, is given by the expected excess return on the market, scaled by asset i's covariation with the pricing kernel relative to the market's covariation with $\mathcal{M}(R)$,

$$\mathbb{E}_0^{\mathbb{P}}[R_i] = \underbrace{\frac{Cov_0^{\mathbb{P}}(\mathcal{M}, R_i)}{Cov_0^{\mathbb{P}}(\mathcal{M}(R), R)}}_{\text{`true beta'}} \mathbb{E}^{\mathbb{P}}[R], \tag{6}$$

where we refer to the ratio of pricing kernel covariances as the 'true beta'. If instead we use the first-order approximation $\mathcal{M}_1(R)$ for the pricing kernel, the asset's expected excess return is given by the standard CAPM beta multiplied by the market risk premium,

$$\begin{aligned} \mathbb{E}_0^{\mathbb{P}}[R_i] &\approx \frac{Cov_0^{\mathbb{P}}(a_1 + b_1 R, R_i)}{Cov_0^{\mathbb{P}}(a_1 + b_1 R, R)} \mathbb{E}_0^{\mathbb{P}}[R] \\ &= \underbrace{\frac{Cov_0^{\mathbb{P}}(R, R_i)}{V_0^{\mathbb{P}}[R]}}_{\text{CAPM beta}} \mathbb{E}_0^{\mathbb{P}}[R]. \end{aligned} \tag{7}$$

[5]The coefficients in the linear and quadratic forms in Equations (7) and (8) arise from a polynomial expansion of $\mathcal{M}$ in a L^2 space weighted with the $\mathbb{P}$-measure density of R. See Schneider (2015) for their structure.

The second-order approximation, which corresponds to the skew-aware CAPM, yields an expected excess return of

$$\mathbb{E}_0^{\mathbb{P}}[R_i] = \frac{Cov_0^{\mathbb{P}}(a_2 + b_2 R + c_2 R^2, R_i)}{Cov_0^{\mathbb{P}}(a_2 + b_2 R + c_2 R^2, R)} \mathbb{E}_0^{\mathbb{P}}[R]$$
$$= \underbrace{\frac{b_2 Cov_0^{\mathbb{P}}(R, R_i) + c_2 Cov_0^{\mathbb{P}}(R^2, R_i)}{b_2 V_0^{\mathbb{P}}[R] + c_2 Cov_0^{\mathbb{P}}(R, R^2)}}_{\text{'skew-adjusted beta'}} \mathbb{E}_0^{\mathbb{P}}[R]. \tag{8}$$

Comparing Equations (8) and (7) illustrates that the 'skew-adjusted beta' accounts for higher-moment risk by additionally incorporating the covariations of the firm's and the market's returns with the squared market return. In other words, a firm's market risk also explicitly depends on how its stock reacts to extreme market situations (i.e. situations of high market volatility) and whether its reaction is disproportionally strong or weak compared to the market itself. A firm that performs comparably well (badly) in such extreme market situations, has a skew-adjusted beta that is lower (higher) relative to its CAPM beta.[6] In other words, as emphasized by Kraus and Litzenberger (1976) and Harvey and Siddique (2000), investors require comparably lower (higher) expected equity returns for firms that are less (more) coskewed with the market. The conceptual and empirical question of this paper is to explore the extent to which accounting for higher order risks such as skewness adds to our understanding of low risk anomalies associated with the CAPM beta and measures of volatility.

In the next Section we examine how the higher moments of a firm's equity return distribution relate to the asset pricing implications discussed above within a structural model that accounts for skewness through default risk.

2.2 Corporate credit risk as a source of skewness

A natural source of time-varying skewness in stock returns is corporate credit risk. To develop this idea, we use the model of Merton (1974) and show how credit risk matters for the shape of a firm's equity return distribution. With the asset value dynamics accounting for systematic and idiosyncratic shocks, we explore the impact of higher moments on expected

[6] For instance, previous research shows that episodes of high volatility in the S&P 500 are typically associated with negative returns, i.e. that $Cov_0^{\mathbb{P}}(R, R^2) < 0$. A firm that is not as prone to negative returns when market volatility is high compared to the S&P 500 itself should have a skew-adjusted beta that is lower than its CAPM beta.

equity returns within the framework discussed above in Section 2.1. Specifically, we show that CAPM-betas increasingly overestimate a firm's true market risk as the firm's credit risk increases or, equivalently, as its ex-ante skewness becomes more negative.

2.2.1 Credit risk and skewness in the Merton model

In the model of Merton (1974), the asset value (A) is governed by a geometric Brownian motion with drift μ and volatility σ. The firm's debt is represented by a zero-coupon bond with face value D and time-to-maturity T and, accordingly, the firm is in default if $A_T < D$ at maturity. Equity (E) represents a European call option on the firm's assets with strike equal to D and maturity T. Its payoff is given by the residual of the asset value minus face value of debt at maturity, i.e. $E_T = \max(A_T - D, 0)$, and its dynamics can be derived using standard Ito calculus. The expected return and the volatility of equity depend on the parameters of the asset value process (i.e. μ and σ) and on the firm's leverage (which we define as D/A). Specifically, we assume that the asset price of a firm evolves according to

$$\frac{dA_t}{A_t} = \mu dt + \sigma(\rho dW_t^{\mathbb{P}} + \sqrt{1-\rho^2} dB_t^{\mathbb{P}}), \tag{9}$$

where the Brownian motion $W_t^{\mathbb{P}} = \xi W^{1\mathbb{P}} + \sqrt{1-\xi^2} W^{2\mathbb{P}}$ is the same as in the dynamics of the market in Equation (1) above, and $B^{\mathbb{P}}$ is a Brownian motion independent of $W^{\mathbb{P}}$. Hence, this specification accommodates systematic and idiosyncratic risk through $W^{\mathbb{P}}$ and $B^{\mathbb{P}}$, respectively.

Accounting for the possibility that a firm can default implies important differences compared to the framework of Black and Scholes (1973), where equity (rather than assets) is assumed to follow a geometric Brownian motion. In structural models, equity itself is an option on the underlying assets and, hence, its value can drop to zero (an impossibility in the Black Scholes world) at maturity, and its return distribution features time-varying volatility and skewness. Figure 1 illustrates these effects by contrasting the Merton model-implied equity price and log return densities (under the risk-neutral probability measure) to that of a comparable Black Scholes valuation, matched by their respective at-the-money implied volatilities. While Merton- and Black Scholes-implied distributions are virtually indistinguishable for firms with low credit risk (low leverage, Panel a), they are markedly different for firms with high credit risk (high leverage, Panel b). The increased probability that the Merton-implied equity price reaches zero for highly leveraged firms affects the entire shape of the distribution. Most notably, it induces a pronounced negative skew in the return distribution that reflects the increased default probability.

The effects are very similar when considering low compared to high asset volatility (σ) scenarios, which have a similar impact in terms of default probability, and the patterns are the same under the $\mathbb{P}$-measure. Figure 2 summarizes these distributional features by plotting the firm's ex-ante ($\mathbb{Q}$-measure) as well as its expected realized ($\mathbb{P}$-measure) variance and skewness for different levels of leverage and asset volatility. Higher credit risk is associated with higher ex-ante variance and more negative ex-ante skewness. Similarly, we see that expected realized variance increases with credit risk and that expected realized skewness becomes more negative with rising leverage and asset volatility.

2.2.2 Expected equity returns

As discussed above, the equity of firm i is a European call option on the firm's assets, which pays off $E_{i,T} = \max(A_{i,T} - D_i, 0)$. Consistent with our discussion in Section 2.1, we denote the forward value of equity by $F_{i,t,T}$, which can be priced by the stochastic discount, i.e.

$$F_{i,t,T} = \mathbb{E}_t^{\mathbb{P}} \left[\mathcal{M} \, F_{i,T,T} \right], \tag{10}$$

where $F_{i,T,T} = E_{i,T}$. We denote firm i's return on equity in excess of the riskfree rate by $R_i := \frac{E_{i,T}}{F_{i,t,T}} - 1$. The expected excess return ($\mathbb{E}_0^{\mathbb{P}}[R_i]$) is given by the product of the market risk premium ($\mathbb{E}_0^{\mathbb{P}}[R]$) multiplied by the firm's 'true beta', i.e. scaled by the firm's and the markets relative covariation with the pricing kernel, as shown in Equation (6). The first-order approximation to $\mathbb{E}_0^{\mathbb{P}}[R_i]$ uses the CAPM beta from Equation (7), the second-order approximation is to use the 'skew-adjusted' beta from Equation (8). Within our framework, we can compute the true beta and assess how the CAPM beta and skew-adjusted beta deviate from the true beta. Since we find that the skew-beta is very similar to the true beta, we focus our discussion on how credit risk-induced skewness affects differences between CAPM and skew-adjusted betas.

More technically speaking, we explore how credit risk/skewness affects the joint distribution of the firm equity and market returns. The left column in Figure 3 shows that the CAPM betas increases with credit risk (i.e. with leverage and/or asset volatility) and the firm's assets' market correlation ρ_i (which is low in Panel a and high in Panel b). Taking a closer look at the CAPM beta components reveals that the correlation of firm stock returns and market returns (right column) decreases as leverage and asset volatility increase. In other words, while the CAPM beta increases with credit risk because of the firm's elevated equity volatility, the firm's equity returns become more idiosyncratic as judged by their market correlation. Referring to the terminology used in option pricing, the delta of the call option (i.e. equity) decreases as its moneyness decreases (i.e. with higher credit risk) and hence equity returns become less related to the underlying (i.e. the firm's assets, which are correlated with the market by ρ_i).

Figure 4 illustrates the impact of skewness on expected equity returns by comparing the firm's CAPM beta, (β_i^{CAPM}) as given in Equation (7), to its skew-adjusted beta, $\beta_i^{skew-adj}$ as given in Equation (8). In the left column, we plot beta deviations measured as $\beta_i^{skew-adj}/\beta_i^{CAPM} - 1$, and these deviations are generally negative implying that the skew-adjusted beta is generally lower than the CAPM beta. The beta deviations become more negative the higher the firm's leverage or asset volatility, which reflects that firms become (comparably) less connected to extreme market situations the more negatively skewed their returns. This implies, consistent with the arguments of Kraus and Litzenberger (1976) and Harvey and Siddique (2000), that firms which are less coskewed with the market require comparably lower expected returns. To make this point more explicit, we compute the skew component of expected equity returns as $\mathbb{E}^{\mathbb{P}}\left[R_i^{skew}\right] = (\beta_i^{skew-adj} - \beta_i^{CAPM}) \times \mathbb{E}^{\mathbb{P}}[R]$. The right column of Figure 4 shows that $\mathbb{E}^{\mathbb{P}}\left[R_i^{skew}\right]$ decreases the higher the firm's credit risk. In other words, the lower (higher) the firm's ex-ante skewness the lower (higher) the compensation for skewness.

Overall, these results illustrate how default risk-induced skewness impacts on the joint distribution of firm equity and market returns. Using the CAPM as an approximation to the true pricing kernel, and thereby ignoring higher moments of the return distribution, leads to an increasing overestimation of the firm's market risk and expected equity returns the higher the firm's credit risk and the higher the correlation of its assets with the market. These model results have direct implications for low risk anomalies, on which we elaborate in detail in the next section.

2.3 Implications for Low Risk Anomalies

The main focus of this paper is to provide insights for low risk anomalies that previous research associates with apparently anomalous equity returns relative to stocks' risk as judged by CAPM betas and measures of (idiosyncratic) equity volatility. Our theoretical results imply that such low risk anomalies may arise from model misspecification (by not accounting for higher moments) and become more pronounced the more negative the skewness of firms' equity returns. Below, we examine the direct links between model implications and empirical low risk anomalies and provide further support for our claims based on data simulated from the model.

Betting against beta. Empirical evidence documents that stocks with low CAPM betas outperform high beta stocks, in stark contrast to the CAPM-implied risk-return-tradeoff. The empirical failure of the CAPM has been explored from different angles and with different objectives over the past decades (see, e.g., Fama and French, 2004, among many others). In a recent paper, Frazzini and Pedersen (2014) assess the anomaly by a betting-against-beta (BaB) strategy that buys low beta stocks and sells high beta stocks and find that BaB generates significantly positive risk-adjusted returns. In our model, the expected returns of BaB strategies are directly connected to ex-ante skewness.

From Figure 3 in the previous section, we know that, for given asset volatility and leverage, CAPM betas increase with the correlation of the firm's assets with the market. For given credit risk, the BaB-strategy therefore entails buying stocks with low and selling stocks with high correlation of firm assets with the market. The alpha of this BaB-strategy, i.e. its expected return in excess of compensation for market covariance risk, is directly determined by the firms' difference in compensation for skewness (i.e. $\mathbb{E}^{\mathbb{P}}\left[R_i^{skew}\right]$ as plotted in Figure 4) of the low correlation firm minus the skew compensation for the high correlation firm. Figure 5 shows that these model-implied BaB alphas are generally positive and increase with firms' asset volatility and leverage. Panel (a) presents BaB alphas for the model parameterization used so far with the low and high correlation being 0.3 and 0.8, respectively. For Panel (b), we use low correlation stocks with $\rho = 0.05$ to illustrate that BaB alphas increase with the gap between asset correlations of long and short BaB stocks.

We also illustrate these cross-sectional implications based on portfolio sorts using data that we simulate from our model; Appendix A describes the setup of the simulation study, that is designed to match key properties of our empirical data such as the cross-sectional distribution of leverage, in more detail. Panel (a) of Figure 6 shows, first, that the portfolio of stocks with highest (lowest) betas generates lowest (highest) alphas. Second, the simulation results confirm that the alpha of the BaB-strategy is directly connected to ex-ante skewness.

Overall, our model suggests that the returns to buying low and selling high beta stocks can be related to (credit risk-induced) return skewness. The higher firms' credit risk, the higher the proneness of CAPM betas to overestimation for high beta stocks. As a consequence, returns of such high CAPM beta stocks appear too low when benchmarked against the CAPM, whereas they exactly compensate for the firm's true market risk. More precisely, our model implies that BaB strategies should be most profitable for firms with most negative skewness but may not deliver excess returns for firms whose returns exhibit very little skewness.

High idiosyncratic volatility predicts low equity returns. Another empirical finding that seems difficult to reconcile with standard asset pricing theories is that idiosyncratic volatility negatively predicts equity returns. Ang et al. (2006) provide such evidence by estimating idiosyncratic volatility from the residual variance of regressing firm equity excess returns on the three Fama French factors.

Measures of idiosyncratic volatility are intrinsically linked to pricing errors of asset pricing models. Our model implies that stocks with high CAPM betas are prone to overestimating expected returns and as a result the pricing errors should predict equity returns with a negative sign. Given that high beta stocks, other things equal, exhibit higher volatility and that our results suggest overestimation to be more pronounced for high compared to low beta stocks, high (low) beta stocks have comparably higher (lower) pricing error variance. As a result idiosyncratic volatility relative to the CAPM should predict negative equity returns, and more so, the more negative skewness (the higher credit risk). Figure 6 provides evidence supporting these claims based on data simulated from our model (for details of the simulation setup see Appendix A). We measure idiosyncratic volatility from past CAPM pricing errors and find that stocks with highest idiosyncratic volatility generate the most negative alphas and that the inverse relation between idiosyncratic volatility and alphas is most pronounced for stocks with most negative ex-ante skewness.

Total volatility and ex-ante variance. Ang et al. (2006) also find that total volatility negatively relates to subsequent equity returns, and, similarly, Conrad et al. (2013) provide evidence that option-implied ex-ante variance negatively predicts stock returns. The same arguments as for BaB and idiosyncratic volatility also suggest that the negative relation between ex-ante variance and stock returns should be most pronounced for firms with most negative skewness: because variance increases as skewness becomes more negative, high variance predicts low risk-adjusted equity returns in our model-world.

2.4 Extension of the model

Our theoretical framework features skewness through a credit risk channel and in our empirical analysis we measure skewness from equity options. Numerous studies confirm that equity options indeed contain information about a firm's default risk, thereby providing evidence that supports such a credit risk channel (see e.g. Hull et al., 2005; Carr and Wu, 2009, 2011; Culp et al., 2014). Previous research, however, also shows that skewness may originate from sources other than default risk, for instance, sentiment (e.g., Han, 2008), demand pressure in options markets (Gârleanu et al., 2009), or differences in beliefs (Buraschi et al., 2014); the latter also discuss the interaction of disagreement and credit risk. More generally, and in contrast to the aggregate market, the skewness of individual firms' stock returns is often positive; recent studies providing evidence on the properties of skewness across firms and in the aggregate market include Albuquerque (2012) and Engle and Mistry (2014). We now show that extending our model to allow for positive skewness does not affect our conclusions on how skewness matters for understanding low risk anomalies.

To allow for positively skewed equity returns, we extend the firm's asset process from its original specification in Equation (9) to incorporate jumps and stochastic volatility,

$$\begin{aligned} d\log A_t &= \left(\mu - \frac{\sigma_t^2}{2}\right) dt + \sigma_t \left(\rho dW_t^{\mathbb{P}} + \sqrt{1-\rho^2} dB_t^{\mathbb{P}}\right) + \eta dJ_t^{\mathbb{P}}, \\ d\sigma_t^2 &= (\nu_2 + \nu_3 \sigma_t^2 + \nu_4 \kappa_t^2) dt + \psi \sigma_t dB_t^{\mathbb{P}}, \end{aligned} \tag{11}$$

where J is a pure jump process with intensity ω and η is a constant; as before $W_t^{\mathbb{P}} = \xi W^{1\mathbb{P}} + \sqrt{1-\xi^2} W^{2\mathbb{P}}$ and κ_t^2 is the stochastic market variance from Equation (1). Using Equation (11), we consider two particular specifications. In the first, the variance of assets remains deterministic (i.e., $\psi = 0$) but we allow for upward jumps in asset returns (i.e., $\omega > 0$ and $\eta > 0$).[7] The second specification features stochastic variance, which may co-move with the stochastic market variance, but excludes jumps (i.e., $\omega = 0$ and $\psi > 0$).

For both specifications, we simulate data that matches our sample in terms of time-series and cross-sectional dimensions. Figure 7 shows (in Panel a) that both simulated samples contain firms with negative and positive ex-ante skewness, with the median individual firm skew being positive for the jump- as well as the stochastic volatility-specification. In line with our discussion of the baseline model above, Panels (b) and (c) show that low risk anomalies are related to skewness: the alphas of betting against beta and betting against idiosyncratic volatility increase with the downside risk of firms. These results show that the skew-implications for low risk anomalies remain the same when allowing for more general cross-sectional distributions of firm equity skewness that match the properties of empirical data.

3 Setup of Empirical Analysis

This Section details that data used in the empirical analysis, describes the estimation of ex-ante variance and ex-ante skewness from equity option data, and discusses the construction of beta-, volatility-, and coskewness-measures from historical stock returns.

3.1 Data

The data set for our empirical analysis of US firms is constructed as follows. The minimum requirement for firms to be included is that equity prices and equity options are available at a daily frequency. We start with options data from OptionMetrics and keep the firms for which we find corresponding equity and firm data in CRSP and Compustat, respectively. Below we describe the construction of variables and related selection criteria that we apply to ensure

[7] Such upward jumps may, for instance, be associated with growth options. We focus here on upward jumps only because downward jumps have a skew-effect very similar to that of default risk described above.

sufficient data quality in detail. Our final data set contains 400,449 monthly observations across 4,967 firms from January 1996 to August 2014.

3.2 Measuring ex-ante variance and skewness

Harvey and Siddique (2000) measure all covariances in Equation (8) from historical stock returns but also discuss that evaluating ex-ante moments using historical data provides imperfect measures. Recent research shows that model-free measures of a firm's higher equity moments implied by stock options are more accurate. While option-implied ex-ante moments can be measured on an individual firm level, options on the cross-moments of stock returns generally do not exist. However, our theoretical model in Section 2.2 suggests that firms' ex-ante skewness is directly linked to firms' coskewness and we draw on this insight in our empirical analysis. We therefore use option-implied information (rather than historical data) in a model-free way (rather than assuming a parametric correlation framework) to explore how firms' ex-ante skewness affects the joint distribution of their stock returns with the market and the prevalence of low risk anomalies.

Building on the concepts of Breeden and Litzenberger (1978) and Neuberger (1994), recent research proposes to assess ex-ante moments of the equity return distribution based on equity option prices. The fundamental idea is that differential pricing of a firm's equity options across different strike prices reveals information about the shape of the risk-neutral return distribution (see, e.g., Bakshi and Madan, 2000). By now, a large literature discusses options-implied measures of ex-ante moments as well as corresponding realizations and associated risk premia (for instance, Bakshi et al., 2003; Carr and Wu, 2009; Todorov, 2010; Neuberger, 2013; Kozhan et al., 2013; Martin, 2013; Schneider and Trojani, 2014; Andersen et al., 2015).

The common theme across these papers is to measure ex-ante variance as an option portfolio that is long in OTM put and OTM call options, and ex-ante skewness as an option portfolio that takes long positions in OTM calls and short positions in OTM puts. Important differences in approaches arise from the associated portfolio weights and the behavior of moment measures when the underlying reaches a value of zero.[8] In these respects, the

[8]With respect to the latter, see for instance the discussion in Martin (2013). The contract underlying the VIX implied volatility index, for example, becomes infinite as soon as the price of the underlying S&P 500 touches zero. Also OTC variance swaps which pay squared log returns have been reported to cause

approach of Schneider and Trojani (2014) appears most suitable to our objective of studying higher moments of individual firms. First, their option portfolio weights specification for variance and skewness comply with the notion of put-call symmetry as developed by Carr and Lee (2009); this is important because this concept connects the observable slope of the implied volatility surface to the unobservable underlying distribution. Second, their measures are well-defined when the stock price reaches zero, a feature that is essential to our setup given that we directly link skewness to default risk.

Schneider and Trojani (2014) suggest to measure variance and skewness as follows.[9] Denote the price of a zero coupon bond with maturity at time T by $p_{t,T}$, the forward price of the stock (contracted at time t for delivery at time T) by $F_{t,T}$, and the prices of European put and call options with strike price K by $P_{t,T}(K)$ and $C_{t,T}(K)$ on the stock, respectively. The portfolios of OTM put and OTM call options that measure option-implied variance ($VAR^{\mathbb{Q}}_{t,T}$) and skewness ($SKEW^{\mathbb{Q}}_{t,T}$) are given by

$$VAR^{\mathbb{Q}}_{t,T} = \frac{2}{p_{t,T}} \left(\int_0^{F_{t,T}} \frac{\sqrt{\frac{K}{F_{t,T}}} P_{t,T}(K)}{K^2} dK + \int_{F_{t,T}}^{\infty} \frac{\sqrt{\frac{K}{F_{t,T}}} C_{t,T}(K)}{K^2} dK \right), \tag{12}$$

and

$$SKEW^{\mathbb{Q}}_{t,T} = \frac{1}{p_{t,T}} \left(\int_{F_{t,T}}^{\infty} \log\left(\frac{K}{F_{t,T}}\right) \frac{\sqrt{\frac{K}{F_{t,T}}} C_{t,T}(K)}{K^2} dK - \int_0^{F_{t,T}} \left(\log \frac{F_{t,T}}{K}\right) \frac{\sqrt{\frac{K}{F_{t,T}}} P_{t,T}(K)}{K^2} dK \right). \tag{13}$$

As can be seen from Equation (13), $SKEW^{\mathbb{Q}}_{t,T}$ is constructed precisely to measure deviations from put-call symmetry and whether $SKEW^{\mathbb{Q}}_{t,T}$ is positive or negative depends on the relative prices of OTM put and OTM call options. The realized counterparts for variance and skewness can be measured from the returns on the underlying stock between t and T; we delegate details to Appendix B.

In our empirical analysis, we measure option-implied moments from OTM equity options with a maturity of 30 days. We define ex-ante variance $VAR_{t,T}$ as the option-implied variance

difficulties in particular in the single-name market.

[9] The exposition below rests on the assumption that options markets are complete, but only for notational convenience. In our empirical analysis we use the 'tradable' counterparts which are computed from available option data only; see Schneider and Trojani (2014). In other words, they account for market incompleteness and do not require interpolation schemes to satisfy an assumption that a continuum of option prices is available.

given in Equation (12). To measure ex-ante skewness $SKEW_{t,T}$, we use the option-implied skew from Equation (13) and appropriately standardize it by variance such that our measure is closer to central skewness, i.e. we define $SKEW_{t,T} := SKEW^{\mathbb{Q}}_{t,T}/VAR^{\mathbb{Q}\,(3/2)}_{t,T}$. In other words, by scaling the position taken in the options portfolio in Equation (13), we can measure skewness effects net of variance effects.[10]

3.3 Construction of variables based on historical stock returns

In our empirical analysis we explore whether accounting for skewness improves our understanding of low risk anomalies. We estimate the risk-measures associated with these anomalies exactly as in the studies that have established these empirical patterns; therefore, to conserve space, we delegate details to Appendix C. We estimate ex-ante CAPM betas exactly as described in Frazzini and Pedersen (2014). For our empirical analysis related to idiosyncratic volatility, we estimate idiosyncratic volatility following Ang et al. (2006) and from CAPM beta estimation as described. above. Using the CAPM residuals is conceptually closer to our theoretical setup as these residuals can be directly interpreted as pricing errors of the CAPM approximation to our asset pricing model in Section 2. Empirically, the results are very similar using either estimate of idiosyncratic volatility. In our discussion of the link between ex-ante skewness and coskewness, we compute the covariance between firm stock returns and squared market returns, i.e. $Cov^{\mathbb{P}}_0(R^2, R_i)$ in Equation (8), as well as the coskewness measures of Kraus and Litzenberger (1976) and Harvey and Siddique (2000).

4 Empirical results

This Section reports our empirical results and provides evidence that beta- and volatility-related low risk anomalies can be rationalized as capturing skew risk-induced return information ignored by asset pricing models such as the CAPM. The empirical patterns concisely match the predictions of the model presented in Section 2. Specifically, we show that ex-ante skewness conveys information for the distribution of future equity returns (Section 4.1) and that the prevalence of low risk anomalies depends on the skewness of the firms' underlying

[10]Central skewness is defined as the third moment of a standardized random variable (subtracting the mean and dividing by the standard deviation). This standardization assesses skewness independently of the effect that unscaled skewness is usually high in absolute terns when variance is high.

return distributions (Section 4.2). Since skewness can be directly connected to default risk, our results also provide insights for the distress puzzle (Section 4.3).

4.1 Ex-ante skewness and the distribution of future equity returns

In this section, we document that ex-ante skewness contains information for the distribution of future equity returns. Figure 8 summarizes our findings by showing that ex-ante skewness positively predicts, both, realized skewness and risk-adjusted stock returns.

To assess the cross-sectional relation of ex-ante skewness to the future equity return distribution, we sort firms into decile portfolios at the end of every month. P_1 contains firms with highest skewness, P_{10} contains firms with lowest (most negative) skewness. Hence, P_{10} contains the firms for which put options are most expensive relative to call options. Table 1 complements Figure 8 by presenting details on the risk characteristics and the risk-adjusted equity returns of the skew portfolios.

We first show, in Panel A of Table 1, that firms' ex-ante skewness is inversely related to estimates of firms' coskewness with the market. Firms with high (low) ex-ante skewness have most (least) negative coskewness as measured by the covariance of their stock returns with squared market returns as well as the coskewness measures of Kraus and Litzenberger (1976) and Harvey and Siddique (2000). These patterns are consistent with our model's prediction that firm's with lowest ex-ante skewness are comparably less connected to extreme market situations. Therefore, our results that stock returns decline from P_1 to P_{10} are consistent with the notion that stocks that add more negative coskewness to an investor's portfolio should be associated with higher expected returns.

Panel A also reports portfolio sample averages for conditional CAPM betas, idiosyncratic volatility, and ex-ante variance, as well as firm size and book-to-market ratios. Looking at these risk characteristics, we find that the variation patterns are distinct but that high ex-ante skewness is typically associated with more risk as judged by these characteristics. However, the dispersion of these risk characteristics relative to their sample distribution is generally low, which suggests that ex-ante skew conveys information beyond these other risk proxies.[11]

[11] Consider, for instance, the estimates of CAPM beta, which decline (non-monotonically) from P_1 to P_{10}, within a range of 0.93 and 1.14. The corresponding sample distribution has a mean of 1.08 with a standard deviation of 0.33, and the 5% and 95% quantiles given by 0.65 and 1.68, respectively.

Panel B provides details on the positive relation between ex-ante skewness and subsequent equity returns for equally-weighted portfolios. High skew firms (P_1) earn a monthly excess return of 1.54% whereas low skew firms only earn 0.14%. The high-minus-low return differential (HL) of 1.40% per month is highly significant. Controlling for standard risk factors, we find that HL factor model alphas are highly significant as well. The four factor alpha (FF4), controlling for market, size, book-to-market, and momentum as suggested by Fama and French (1993) and Carhart (1997), is 1.36% per month, resulting from alphas of 0.82% in P_1 and -0.54% in P_{10}, respectively. These patterns are consistent with the notion that realized skewness and equity returns have to be positively related (as also illustrated in Figure 8) and suggest that investors demand lower returns for stocks that are less coskewed with the market.

We repeat our analysis using value-weighted portfolios and report the results in Panel C. The HL returns are slightly lower compared to the equally-weighted portfolios but highly significant, with a FF4 alpha of 1.16% per month (compared to 1.36% for equally-weighted portfolios). Finding that results are very similar for both portfolio-weighting schemes shows that our results are not driven by firm size.

Overall, our findings provide strong evidence that ex-ante skewness contains information for the distribution of future equity returns, consistent with the model developed in Section 2. These results lend support to earlier research that suggests to incorporate higher moment preferences in asset pricing to account for negative return premia on coskewness (as advocated by, e.g., Kraus and Litzenberger, 1976; Harvey and Siddique, 2000). In what follows, we show that understanding the link between ex-ante skewness and the equity return distribution provides insights for beta- and volatility-related low risk anomalies (Section 4.2) as well as for the distress puzzle (Section 4.3).

4.2 Low risk anomalies

Previous research documents that high CAPM beta stocks underperform low beta stocks (e.g., Haugen and Heins, 1975; Frazzini and Pedersen, 2014) and that (idiosyncratic) volatility negatively predicts equity excess returns (e.g., Ang et al., 2006; Conrad et al., 2013). In this section, we provide evidence that accounting for firms' skewness adds to our understanding of such low risk anomalies. Figure 10 summarizes our main findings by showing that trading on these low risk anomalies is most profitable among firms with very negative skewness but does not generate significant excess returns among firms with high ex-ante skewness.

Our finding that the prevalence of low risk anomalies is related to return skewness is consistent with the model implications derived in Section 2. With these results to be detailed below, we first take a look at low risk anomalies in our data.[12] Figure 9 verifies that betting against beta and idiosyncratic volatility delivers positive risk-adjusted returns in line with previous research. More specifically, we use equally-weighted quintile portfolios sorted by CAPM betas, idiosyncratic volatility relative to the CAPM and relative to the Fama-French three factor model, and measures of ex-ante variance. We find that four factor alphas are lowest in the high beta/volatility portfolios (P_1) and increase towards the high risk portfolio (P_5), with betting against risk (BaR) alphas in the range of 0.3% and 0.5% per month.

To test the predictions of our model, we conduct unconditional portfolio double sorts. Independently of the beta/volatility-sorts above, we also sort firms into quintile portfolios according to their skewness, with high (low) skew firms in Skew-P_1 (Skew-P_5), respectively. Interacting the skew portfolios with the beta/volatility portfolios (P_1 to P_5) in an unconditional double sort yields a total of 25 portfolios per combination of ex-ante skewness and beta/volatility-measure. Within each skew portfolio s, we compute the equally-weighted returns of betting against risk from being long the low beta/volatility portfolio (the intersection of Skew-$P_s \times P_5$) and being short the high beta/volatility portfolio (the intersection of Skew-$P_s \times P_1$). Figure 10 suggests that the profitability of betting against beta/volatility is strongly related to return skewness.

Table 2 provides detailed statistical results. As a benchmark, the first two columns report the returns to betting against beta/volatility without controlling for skewness. All factor model alphas are positive, all FF3 alphas are significant at least at the 5% level, but there is some variation for FF4 alphas. The remaining columns report results for the unconditional portfolio double-sorts. In the high skew portfolio (Skew-P_1), betting against beta/volatility delivers negative raw excess returns, in some cases marginally significant FF3 alphas, but FF4 alphas are generally very close and statistically not different from zero. Moving to the

[12] Such a first check seems warranted because our dataset differs from those used in the studies that have established these anomalies. Differences in data arise because our empirical setup requires the use of options data, which is only available from 1996 and does not cover all firms in the CRSP-Compustat-universe. As a consequence, our sample period starts later than that of Ang et al. (2006) whose sample starts from 1963 and Frazzini and Pedersen (2014) who use data back to 1926.

low skew portfolios, raw returns and factor model alphas increase and become significant. Comparing the performance of betting against beta/volatility across skew portfolios reveals that the low minus high skew portfolio differential ($P_5 - P_1$) delivers a four factor alpha of 1.15% to 1.76% per month across portfolios sorted by CAPM beta, (idiosyncratic) volatility, and ex-ante variance. These results confirm our conjecture that skewness matters for low risk anomalies.

To explore the relation between ex-ante skewness and the variables associated with low risk anomalies from a different perspective, we use the same 25 portfolios to show that betting on skew is profitable in all beta- and volatility portfolios. Table 3 shows that buying high and selling low skew firms generates significant excess returns in all CAPM beta-, idiosyncratic volatility-, and ex-ante variance-sorted portfolios. The returns of betting on skew decrease from the high beta/volatility portfolio (P_1) to the low beta/volatility portfolio (P_5), which is in line with the model's implication that high beta/volatility stocks are most prone to skew effects. The return differential of betting on skew in the high versus low beta/volatility portfolios (HL) equals, by construction of the double-sort setup, the returns of the $P_5 - P_1$-differential Table 2. In other words, betting against beta/volatility risk in low skew firms compared to high skew firms, essentially collects skew-related return differentials in high compared to low beta/volatility stocks. From either perspective, the results confirm that ex-ante skewness conveys return-relevant information not captured by betas and volatilities.

To explore the persistence of the relation between ex-ante skewness and the profitability of betting against beta/volatility, Figure 11 plots the cumulative returns of the $P_5 - P_1$-differential reported in Table 2. The figure clearly suggests that our results are not driven by specific periods in our sample and shows that accounting for skewness delivers steady premia for betting against beta/volatility strategies over time. These results are very similar for equity excess returns (Panel a) as well as four-factor alphas (Panel b).

Our empirical results concisely match the predictions of our model outlined in Section 2: the more negative a firm's ex-ante skew, the more CAPM betas overestimate the firm's true market risk. As a result, equity returns appear low compared to the - too high - CAPM beta, and betting against the overestimated beta generates positive returns. These arguments extend to idiosyncratic volatility estimated from the residuals of CAPM regressions, because these pricing errors are directly affected by the CAPM beta deviations conditional on the skewness of the underlying distribution. Empirically, the same patterns apply to idiosyncratic volatility measured from the Fama-French three factor model and the results for ex-ante variance directly follow from the discussion in Section 2 as well.

Overall, our findings suggest that low risk anomalies can be understood as collecting returns related to higher moment risk not captured by pricing models such as the CAPM. In Section 5 we discuss various robustness checks that corroborate our conclusions, such as the use of value- and rank-weighted returns as well as a repetition of the empirical analysis using the coskewness measure of Harvey and Siddique (2000).

4.3 Insights for the distress puzzle

In our theoretical framework we show that one channel through which skewness matters for the equity return distribution is default risk. It therefore seems natural to also interpret our findings in the context of research that studies the cross-sectional relation between credit risk and equity returns. This literature also faces a low risk anomaly, namely the 'distress puzzle', defined as the lack of a positive relation between distress risk and equity returns (see, e.g., Dichev, 1998; Griffin and Lemmon, 2002; Vassalou and Xing, 2004; Campbell et al., 2008; Friewald et al., 2014). More specifically, Campbell et al. (2008) find that stocks of distressed firms have anomalously low risk-adjusted returns that are associated with high standard deviations and high market betas. These pattern exactly resemble those of beta- and volatility-related low risk anomalies.

In our structural model (Section 2), ex-ante skew is directly tied to the firm's default risk. Empirical research provides strong evidence that a firm's credit risk, e.g. as quantified by premia of credit default swaps (CDS) or corporate yield spreads, is indeed reflected in prices of equity options (see e.g. Hull et al., 2005; Carr and Wu, 2009, 2011; Culp et al., 2014).[13] To see whether our empirical results based on option-implied skewness can be directly connected to credit risk, we first compute leverage differentials across skew-sorted quintile and decile portfolios. Panel A of Table 4 shows that firms with high skewness have significantly lower book leverage and lower market leverage than firms with low skewness.[14] It therefore seems

[13] Campbell and Taksler (2003) can be viewed as a precursor to this recent stream of research; they show that there is a strong empirical relation between equity volatility and corporate bond yields.

[14] While the leverage differentials may not appear very large in economic terms, one has to bear in mind that information on leverage can only be updated at a lower frequency (usually once a year) and that leverage adjustments do not occur very frequently.

legitimate to also interpret our results on skew-sorted portfolios in a credit risk context as suggested by our model.

Next, we evaluate the equally- and value-weighted returns of leverage-sorted quintile and decile portfolios and present results in Panels B and C of Table 4. In line with previous research, we find a pronounced distress puzzle in our data for value-weighted portfolios: the returns to buying high and selling low leverage firms are negative and the corresponding four-factor alphas are significantly negative, i.e. correcting for risk using standard factors worsens the performance of high leverage relative to low leverage firms. This pattern, which is the same but statistically not as pronounced for equally-weighted portfolios, is perfectly in line with the predictions of our model: Figure 4 shows that the skew-related return component beyond compensation for market covariance risk should decrease the higher a firm's leverage. To provide further evidence that these leverage-related risk-adjusted return patterns are indeed related to skewness, we add the HL-returns of the skew-sorted portfolios in Table 1 as an additional factor to the Fama-French-Carhart-regressions. We find that the loadings on this 'skew-factor' (SKEW betas) are significantly negative and that alphas of the skew-augmented FF4-regression (SKEW FF4 alphas) are much smaller (in absolute terms) and become insignificant; the only exception is the value-weighted alpha of the decile portfolios sorted on book leverage which remains marginally significant with a t-statistic of -1.74 (compared to -2.98 without the skew-adjustment).

In their concluding remarks, Campbell et al. (2008) speculate that accounting for skew preferences may help to understand the distress puzzle. Our model and empirical findings support their view by suggesting that firms with high credit risk have most negative ex-ante skewness but exhibit lowest coskewness with the market, which in turn allows them to trade at lower expected returns.

5 Additional results and robustness checks

This section presents further empirical results that corroborate our findings from the core analysis. To conserve space, we delegate most empirical results and Tables of robustness checks to the separate Internet Appendix.

Demand for Lottery: Betting against $MAX5$. In a recent paper, Bali et al. (2015a) argue that taking into account investors' demand for lottery stocks eliminates the returns to betting against beta. They follow Bali et al. (2011) and use $MAX5$, defined as the average of a firm's five highest daily returns over the past month, as a proxy for lottery demand characteristics as identified by Kumar (2009). Given that equity returns decrease with $MAX5$, we repeat our previous beta- and volatility-analyses and assess the returns to betting against $MAX5$ when accounting for ex-ante skewness. The results in Table 5 show that betting against $MAX5$ is generally profitable but also that the returns are significantly higher in the low-skew portfolio (Skew-P_5) compared to the high skew portfolio (Skew-P_1): the raw excess returns and the four-factor alpha are significantly positive with 0.75% per month and 0.68% per month, respectively. Given that the returns to betting against $MAX5$ increase with downside risk but that the skew related return differentials are not as high as for betting against beta/volatility (in Table 2), our results suggest that $MAX5$ partly captures the skew-effect on asset prices.

Robustness: Using the coskewness measure of Harvey and Siddique (2000). In our core analysis, we use option-implied measures of firms' ex-ante skewness to assess the prevalence of low risk anomalies. We choose this empirical approach because our structural model implies that ex-ante skewness is directly related to coskewness and because firms' ex-ante skewness can be directly measured from equity options, which previous research argues to convey more accurate information about higher moments than measures based on historical returns. As a robustness check, we now repeat the empirical analysis using the return-based measure of coskewness suggested by Harvey and Siddique (2000). We find that these results are perfectly consistent with the insight of our model that ex-ante skewness is inversely related to coskewness and that (co)skewness matters for understanding the returns of low risk anomalies.

Table IA.1 presents the equity returns of portfolios sorted by coskewness and shows that firms with highest coskewness (P_1) earn significantly lower returns than firms with lowest coskewness (P_{10}); all factor-models are negative as well but their significance is mixed. These results are consistent with the arguments of Kraus and Litzenberger (1976) that investors accept lower (demand higher) expected returns on assets that add positive (negative) skewness to an investor's portfolio. Table IA.2 presents results for unconditional portfolio double sorts based on firms' coskewness. As expected, these results exhibit exactly the opposite patterns as compared to the double sorts based on firms' ex-ante skewness. While there is some variation in statistical significance, the main insight of our model is highly significant in the data: stocks with high CAPM betas of firms that exhibit highest coskewness with the market (Coskew-P_1) are most prone to overestimation. Accounting for skewness their expected equity returns should have the largest discount relative to CAPM-expected returns because of the positive coskew-effect added to the investor's portfolio. Because the standard CAPM ignores this skew-effect, the returns to betting against beta should deliver the highest returns among firms in Coskew-P_1. Our empirical results confirm for all betting against beta and volatility strategies that the CAPM-, FF3-, and FF4-alphas are highest and most significant in Coskew-P_1.

Robustness: Using lagged option-implied measures. We repeat our empirical analysis using option-implied quantities that are measured on the business day before firms are assigned to skew-sorted and double-sorted portfolios. Tables IA.3 and IA.4 present these results, which show that allowing for an additional lag between signal-generation and portfolio-formation does not affect our results.

Robustness: Double-sort procedure and return-weighting schemes. In the Internet Appendix we present and discuss detailed results which show that our conclusions are robust to changing the number of portfolios used in the unconditional double sorts as well as to changing the return-weighting scheme (see Table IA.5). For value-weighted returns, we find that betting against beta/volatility in low relative to high skew portfolios always generates a positive four-factor alpha but that there is more variation in levels of significance compared to using equally-weighted portfolios. Using rank-weighted portfolios, all skew related return differentials in betting against beta/volatility are highly significant with alphas similar or higher compared to equally-weighted portfolios. Moreover, we show that our results are robust to using conditional double sorts that sequentially assign firms, first, to skew-portfolios and, second, within each skew- portfolio, to beta-/volatility-portfolios (see Table IA.6).

6 Conclusion

This paper provides a novel perspective on beta- and (idiosyncratic) volatility-based low risk anomalies established in previous research. We show that these apparently anomalous empirical patterns may not necessarily pose asset pricing puzzles when accounting for the skewness of the equity return distribution. Our theoretical framework implies that the standard capital asset pricing model (CAPM) overestimates expected stock returns for firms whose return distributions are negatively skewed due to credit risk. More specifically, the more negatively skewed a firm's return distribution, the less the firm's returns are coskewed with the market, and skew-adjusted expected returns are lower than those implied by the CAPM. Low returns to high CAPM beta stocks may therefore just reflect that accounting for skewness is an important feature of asset pricing models. These arguments also provide insights for other seemingly anomalous risk-return-relations, such as the negative link between equity returns and idiosyncratic volatility, which is typically estimated from pricing errors of asset pricing models that do not account for skewness. Given that return skewness is intrinsically linked to firms' default risk, our findings can also be related to the distress puzzle.

Our empirical results confirm the model's prediction that skewness conveys information for the future stock return distribution beyond that embedded in measures of equity volatility and CAPM betas. We find that betting against beta or volatility generates high risk-adjusted excess returns among the firms that exhibit the most negatively skewed return distributions but not among stocks with highest ex-ante skewness. The skew-related return differential of betting against beta/volatility among low compared to high skew firms amounts to 1.15% to 1.76% per month when using CAPM betas, estimates of ex-ante variance, or measures of idiosyncratic volatility relative to the CAPM and relative to the Fama French three factor model. More generally, our theoretical and empirical results lend strong support to previous research emphasizing that higher moment preferences are a key feature for understanding asset prices.

Appendix

A Setup for the simulation study

Our simulation study that forms the basis for the results presented in Figures 6 and 7 (in Sections 2.3 and 2.4) is designed to generate data that matches the properties of our empirical data along several dimensions. In what follows, we sketch the most important steps of this procedure.

To simulate an economy according to the joint model for the market and asset prices from Sections 2.1 and 2.2, we first generate sets of parameters with plausible values. To model the dynamics of the market, we fix the coefficient of relative risk aversion γ at 2, the instantaneous correlation between forward market returns and stochastic variance ξ is set to the value of -0.85, the unconditional mean of index variance to 0.04. From these parameters we discretize the stochastic differential equation (1) and simulate a market time series of 240 months from daily increments.

In a second step, analogously to the market simulation, we generate 2,000 firms for which we draw the parameters from distributions reflecting the observed cross section. We draw $\rho \sim \mathcal{U}(0,1)$, a uniform distribution on the unit interval, leverage $D \sim \mathcal{B}(2,5)$, a Beta distribution, the asset drift $\mu \sim \Gamma(2, 0.01)$, from a Gamma distribution, same as the volatility of asset variance ψ, which is taken as the square-root of a $\Gamma(2, 0.01)$ random variable. The parameters ν_2, ν_3, ν_4 are drawn from Gamma distributions so that the unconditional mean $\mathbb{E}^{\mathbb{P}}\left[\sigma_t^2\right]$ exists. To better reflect the cross section of US corporations we set additionally 25% of the populations leverage to zero (see, e.g., Strebulaev and Yang, 2013) . When simulating the asset value processes, we keep the trajectory of the forward market fixed to ensure it is identical for all assets. Given these sample paths for firm assets, we then compute the sample paths of corporate equity values, equity returns, implied skewness, and CAPM betas.

B Realized variance and skewness

The realized counterparts to the option-implied measures of variance and skewness (see Section 3.2) can be measured from the returns on the underlying stock between t and T. Under a continuum of option prices and dynamic updating of the option portfolios in Equations

(12) and (13), realized variance ($VAR^{\mathbb{P}}_{n,t,T}$) and realized skewness ($SKEW^{\mathbb{P}}_{n,t,T}$) are given by

$$\begin{aligned} VAR^{\mathbb{P}}_{n,t,T} &:= 4\sum_{i=1}^{n} \frac{F_{t_i,T}}{F_{t_{i-1},T}} + 1 - 2\sqrt{\frac{F_{t_i,T}}{F_{t_{i-1},T}}} \\ &= \sum_{i=1}^{n} \left(\log \frac{F_{t_i,T}}{F_{t_{i-1},T}}\right)^2 + O\left(\log \frac{F_{t_i,T}}{F_{t_{i-1},T}}\right)^3, \end{aligned} \tag{B.1}$$

and

$$\begin{aligned} SKEW^{\mathbb{P}}_{n,t,T} &:= 4\sum_{i=1}^{n} \frac{F_{t_i,T}}{F_{t_{i-1},T}} - 1 - \sqrt{\frac{F_{t_i,T}}{F_{t_{i-1},T}}} \log\left(\frac{F_{t_i,T}}{F_{t_{i-1},T}}\right) \\ &= \frac{1}{6}\sum_{i=1}^{n} \left(\log \frac{F_{t_i,T}}{F_{t_{i-1},T}}\right)^3 + O\left(\log \frac{F_{t_i,T}}{F_{t_{i-1},T}}\right)^4. \end{aligned} \tag{B.2}$$

where n denotes the number of realized returns observed between t and T. Equations (B.1) and (B.2) show that the leading orders are quadratic and cubic in log returns for realized variance and realized skewness, respectively. We compute $\mathbb{P}$-variance and -skewness from daily data over the month that follows portfolio formation, i.e. n corresponds to the number of days in the respective month. Our measure of realized skewness $RSKEW_{n,t,T}$ is given by standardizing the estimate of $RSKEW_{n,t,T} := SKEW^{\mathbb{P}}_{n,t,T}/VAR^{\mathbb{P}\,(3/2)}_{n,t,T}$.

C Variables constructed from historical stock returns

In our empirical analysis we explore whether accounting for skewness improves our understanding of low risk anomalies. This Section summarizes how we estimate CAPM betas, idiosyncratic volatility, and coskewness from past equity returns.

CAPM betas. We estimate ex-ante CAPM betas exactly as described in Frazzini and Pedersen (2014). For security i, the beta estimate is given by

$$\hat{\beta_i^{TS}} = \hat{\rho}_i \frac{\hat{\sigma}_i}{\hat{\sigma_m}} \tag{C.3}$$

where $\hat{\sigma_m}$ and $\hat{\sigma}_i$ denote the volatilities for stock i and the market excess returns, and ρ_i denotes their correlation with the market. We estimate volatilities as one-year rolling standard deviations of one-day log returns and correlations using a five-year rolling window of overlapping three-day log returns. As a minimum, we require 120 and 750 trading days of non-missing data, respectively. To reduce the influence of outliers, Frazzini and Pedersen (2014) follow previous research and shrink the time-series estimate $\hat{\beta}_i^{TS}$ to the cross-sectional beta mean ($\hat{\beta}^{XS}$),

$$\hat{\beta}_i = w \times \hat{\beta}_i^{ts} + (1 - w) \times \hat{\beta}^{XS}, \tag{C.4}$$

where they set $w = 0.6$ and $\hat{\beta}^{XS} = 1$. Following this procedure, we generate end-of-month pre-ranking CAPM betas for the period January 1996 to July 2014.

Idiosyncratic volatility. For our empirical analysis, we estimate two series of idiosyncratic volatility. First, we estimate idiosyncratic volatility following Ang et al. (2006) as the square root of the residual variance from regressing daily equity excess returns of firm i on the three Fama French factors over the previous month. As a second estimate, we use the square root of the residual variance resulting from the CAPM beta estimation as described above. Using the CAPM residuals is conceptually closer to our theoretical setup as these residuals can be directly interpreted as pricing errors of the CAPM approximation to our asset pricing model in Section 2. Empirically, the results are very similar using either estimate of idiosyncratic volatility.

Measures for coskewness. To provide evidence that a firm's ex-ante skewness is inversely related to its coskewness with the market, as suggested by our model, we compute three measures of coskewness. We present estimates of the covariance between firm stock returns and squared market returns, i.e. $Cov_0^{\mathbb{P}}(R^2, R_i)$ in Equation (8), as well as the coskewness measure of Kraus and Litzenberger (1976), and direct coskewness as suggested by Harvey and Siddique (2000). All these measures become more negative the more negative skewness a stock adds to an investor's portfolio. Thus, the more negative these measures of coskewness, the higher expected equity returns should be. Similar to CAPM betas, we estimate these measures of coskewness using daily data in rolling one year windows.

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Table 1: Portfolios sorted by ex-ante skewness

This Table summarizes firm characteristics and equity returns across skew-portfolios. At the end of every month, we rank firms based on their ex-ante skewness and assign firms to portfolios, with P_1 (P_{10}) containing firms with highest (lowest) skewness. Panel A presents portfolio sample averages for firms' risk characteristics. We report ex-ante skewness (annualized, in percent), three measures of coskewness ($Cov_0^{\mathbb{P}}(R^2, R_i)$ denoting the covariation of firm equity excess returns and squared market excess returns as well as the coskewness measures of Kraus and Litzenberger (1976) and Harvey and Siddique (2000)), conditional CAPM betas, idiosyncratic volatility estimated from the residual variance of CAPM and Fama French three-factor regressions (both estimates are monthly, in percent), and ex-ante variance (annualized, in percent). Size refers to firms' market capitalization (in billion US dollars) and B/M denotes book-to-market ratios. In Panels B and C, we present the returns of equally-weighted portfolios and value-weighted portfolios, respectively. We report monthly equity returns (in percentage points) for individual portfolios as well as the $P_1 - P_{10}$ differential (HL). We report raw excess returns along with standard deviations and Sharpe ratios (annualized), as well as alphas of CAPM-, Fama-French three-, and four-factor regressions. Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by Andrews (1991). The data covers 4,967 US firms, is sampled at a monthly frequency over the period January 1996 to August 2014, and contains a total of 400,449 observations.

Panel A. Characteristics

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}
Ex-ante skewness	17.37	6.50	2.98	0.65	−1.17	−2.79	−4.41	−6.27	−8.91	−17.60
Coskewness										
$Cov_0^{\mathbb{P}}(R^2, R_i)$	−1.48	−1.54	−1.43	−1.36	−1.30	−1.22	−1.15	−1.06	−0.99	−0.94
Kraus/Litzenberger	−0.96	−0.98	−0.93	−0.89	−0.86	−0.81	−0.78	−0.72	−0.66	−0.61
Harvey/Siddique	−7.33	−6.39	−5.41	−4.17	−3.96	−2.86	−2.89	−2.39	−2.09	−2.45
CAPM beta	1.08	1.14	1.14	1.13	1.11	1.09	1.06	1.02	0.99	0.93
CAPM idio. vol.	3.13	3.34	3.16	2.97	2.77	2.59	2.41	2.25	2.11	2.02
FF3 idio. vol.	2.63	2.77	2.58	2.42	2.24	2.08	1.94	1.80	1.69	1.62
Ex-ante variance	44.19	38.70	32.58	28.13	24.35	21.50	19.09	17.26	15.97	18.07
Size	1.44	1.89	2.57	3.50	4.85	6.17	8.01	10.08	12.57	11.10
B/M	0.56	0.51	0.49	0.47	0.46	0.45	0.45	0.45	0.46	0.50

(continued on next page)

Table 1 *(continued)*

Panel B. Equity returns of portfolios sorted by ex-ante skewness: Equally-weighted

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	HL
Excess return	1.54***	1.39**	0.96*	0.88*	0.78	0.79*	0.76*	0.64	0.47	0.14	1.40***
	[2.71]	[2.47]	[1.90]	[1.85]	[1.60]	[1.74]	[1.75]	[1.55]	[1.21]	[0.40]	[3.85]
Std deviation	8.04	8.05	7.61	7.02	6.68	6.19	5.92	5.45	5.00	4.51	5.20
Skewness	0.51	0.19	−0.26	−0.26	−0.47	−0.51	−0.60	−0.68	−0.73	−1.02	2.25
Sharpe ratio	0.66	0.60	0.44	0.43	0.41	0.44	0.45	0.40	0.32	0.11	0.93
CAPM alpha	0.68**	0.50*	0.10	0.08	−0.00	0.06	0.06	−0.01	−0.12	−0.36*	1.04***
	[2.31]	[1.82]	[0.44]	[0.36]	[-0.01]	[0.30]	[0.35]	[-0.04]	[-0.65]	[-1.69]	[3.57]
FF3 alpha	0.48**	0.35*	−0.04	−0.06	−0.13	−0.09	−0.09	−0.18	−0.29**	−0.57***	1.05***
	[2.07]	[1.73]	[-0.27]	[-0.55]	[-1.11]	[-0.76]	[-0.78]	[-1.48]	[-2.33]	[-4.75]	[3.95]
FF4 alpha	0.82***	0.65***	0.15	0.06	−0.03	−0.01	−0.05	−0.16	−0.25*	−0.54***	1.36***
	[3.56]	[3.58]	[1.17]	[0.52]	[-0.26]	[-0.08]	[-0.39]	[-1.32]	[-1.93]	[-4.88]	[4.60]

Panel C. Equity returns of portfolios sorted by ex-ante skewness: Value-weighted

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	HL
Excess return	1.29***	1.18*	0.96**	1.06**	0.76	0.97**	0.78**	0.68**	0.55*	0.15	1.14***
	[2.65]	[1.78]	[1.99]	[2.32]	[1.60]	[2.46]	[2.01]	[2.01]	[1.70]	[0.46]	[3.12]
Std deviation	8.18	8.96	7.36	6.83	6.58	5.96	5.59	5.01	4.48	4.42	6.41
Skewness	2.13	0.81	0.21	0.09	−0.33	−0.21	−0.35	−0.57	−0.37	−1.02	4.12
Sharpe ratio	0.55	0.45	0.45	0.54	0.40	0.56	0.48	0.47	0.43	0.12	0.62
CAPM alpha	0.53**	0.27	0.17	0.31	0.00	0.28**	0.11	0.08	0.02	−0.34**	0.87***
	[2.03]	[0.77]	[0.77]	[1.30]	[0.00]	[2.11]	[1.01]	[0.61]	[0.18]	[-2.37]	[2.69]
FF3 alpha	0.31	0.17	0.13	0.31	0.02	0.30**	0.12	0.05	0.00	−0.37***	0.68**
	[1.13]	[0.51]	[0.56]	[1.47]	[0.15]	[2.04]	[1.06]	[0.42]	[0.00]	[-2.88]	[2.08]
FF4 alpha	0.82***	0.68**	0.48*	0.58***	0.24	0.51***	0.21*	0.13	0.07	−0.34**	1.16***
	[3.07]	[2.01]	[1.85]	[2.74]	[1.43]	[4.36]	[1.86]	[1.12]	[0.64]	[-2.39]	[3.42]

Table 2: Betting against beta- and (idiosyncratic) volatility in skew-portfolios

This Table reports equity excess returns of betting against beta and volatility. In Panel A, we compute the returns of buying low and selling high CAPM beta stocks (betting against beta). Similarly we compute the returns to buying low risk and selling high risk stocks using idiosyncratic volatility relative to the CAPM (Panel B), idiosyncratic volatility relative to the Fama French three factor model (Panel C), and ex-ante variance (Panel D) as risk measures. In each panel, the first two columns report excess returns of betting against risk using quintile and decile portfolios, respectively. The remaining columns report results from unconditional portfolio double-sorts. We sort firms into equally-weighted quintile portfolios based on their ex-ante skewness, where Skew-P_1 and Skew-P_5 contain firms with highest and lowest ex-ante skewness, respectively. Independent of the skew-sorts, we also sort firms into equally-weighted quintile portfolios based on either their CAPM beta, idiosyncratic volatility, or their ex-ante variance. For every skew portfolio, we compute the returns of betting against risk. The last column reports the $P_5 - P_1$ differential. We report raw excess returns and alphas of CAPM-, Fama-French three-, and four-factor regressions. Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by Andrews (1991). The sample period is January 1996 to August 2014.

Panel A. Betting against CAPM Beta

	Betting against Risk		Betting against Risk in Skew Portfolios					
	5 Port.	10 Port	Skew-P_1	Skew-P_2	Skew-P_3	Skew-P_4	Skew-P_5	$P_5 - P_1$
Excess return	0.07	−0.08	−0.06	0.21	0.21	0.28	0.98	1.04***
	[0.11]	[-0.10]	[-0.09]	[0.37]	[0.35]	[0.45]	[1.64]	[2.73]
Std deviation	8.76	10.59	10.29	8.88	8.24	7.88	7.65	5.87
Skewness	−0.44	−0.50	−0.66	−0.40	−0.23	−0.01	0.19	1.41
Sharpe ratio	0.03	−0.02	−0.02	0.08	0.09	0.12	0.44	0.62
CAPM alpha	0.87**	0.92*	0.82	0.99**	0.93**	1.00**	1.69***	0.87**
	[2.04]	[1.87]	[1.64]	[2.22]	[2.28]	[2.06]	[4.10]	[2.32]
FF3 alpha	0.76***	0.79**	0.75**	0.84***	0.76**	0.89**	1.60***	0.84**
	[2.61]	[2.23]	[1.99]	[2.77]	[2.29]	[2.38]	[4.57]	[2.02]
FF4 alpha	0.42	0.39	0.29	0.52	0.53	0.70*	1.44***	1.15**
	[1.14]	[0.87]	[0.58]	[1.54]	[1.49]	[1.65]	[4.00]	[2.50]

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Table 2 *(continued)*

Panel B. Betting against CAPM idiosyncratic volatility

	Betting against Risk		Betting against Risk in Skew Portfolios					
	5 Port.	10 Port	Skew-P_1	Skew-P_2	Skew-P_3	Skew-P_4	Skew-P_5	$P_5 - P_1$
Excess return	0.15	0.32	−0.21	0.57	0.58	0.76	1.44**	1.65***
	[0.25]	[0.46]	[-0.32]	[0.84]	[0.96]	[1.25]	[2.40]	[4.55]
Std deviation	9.19	10.80	10.00	9.48	8.93	8.71	7.85	5.73
Skewness	−0.63	−0.69	−0.66	−0.69	−0.30	−0.70	−0.31	0.92
Sharpe ratio	0.06	0.10	−0.07	0.21	0.22	0.30	0.64	1.00
CAPM alpha	0.88**	1.22**	0.61	1.29**	1.26***	1.41***	1.99***	1.38***
	[1.99]	[2.47]	[1.33]	[2.31]	[2.93]	[2.87]	[4.40]	[4.22]
FF3 alpha	0.81***	1.17***	0.52*	1.19***	1.20***	1.35***	1.93***	1.41***
	[3.40]	[4.31]	[1.66]	[3.74]	[4.02]	[4.02]	[6.08]	[4.13]
FF4 alpha	0.49	0.79**	0.12	0.96***	1.05***	1.21***	1.70***	1.58***
	[1.67]	[2.33]	[0.34]	[2.83]	[3.23]	[3.27]	[4.79]	[5.12]

Panel C. Betting against FF3 idiosyncratic volatility

	Betting against Risk		Betting against Risk in Skew Portfolios					
	5 Port.	10 Port	Skew-P_1	Skew-P_2	Skew-P_3	Skew-P_4	Skew-P_5	$P_5 - P_1$
Excess return	0.18	0.29	−0.08	0.48	0.45	0.94*	1.12***	1.20***
	[0.35]	[0.49]	[-0.15]	[0.82]	[0.93]	[1.69]	[2.79]	[3.25]
Std deviation	7.98	9.10	8.91	8.32	7.09	7.29	6.52	5.45
Skewness	−0.77	−0.82	−0.65	−1.00	−0.65	−0.47	−0.27	0.38
Sharpe ratio	0.08	0.11	−0.03	0.20	0.22	0.45	0.60	0.77
CAPM alpha	0.81**	1.02**	0.64	1.09**	0.98***	1.49***	1.56***	0.91***
	[2.06]	[2.27]	[1.48]	[2.15]	[2.70]	[3.20]	[3.84]	[2.78]
FF3 alpha	0.75***	0.98***	0.56*	1.00***	0.90***	1.45***	1.60***	1.04***
	[3.58]	[3.72]	[1.85]	[3.40]	[3.60]	[4.44]	[5.58]	[3.41]
FF4 alpha	0.43*	0.57**	0.16	0.77**	0.72***	1.26***	1.37***	1.21***
	[1.80]	[2.26]	[0.52]	[2.44]	[2.74]	[3.48]	[5.77]	[3.90]

Panel D. Betting against ex-ante variance

	Betting against Risk		Betting against Risk in Skew Portfolios					
	5 Port.	10 Port	Skew-P_1	Skew-P_2	Skew-P_3	Skew-P_4	Skew-P_5	$P_5 - P_1$
Excess return	0.02	0.06	−0.33	0.35	0.85	0.73	1.52**	1.85***
	[0.03]	[0.08]	[-0.52]	[0.54]	[1.35]	[1.05]	[2.48]	[5.80]
Std deviation	9.40	11.22	10.17	9.82	9.29	8.84	8.11	5.72
Skewness	−0.86	−0.93	−0.84	−0.94	−0.51	−0.37	−0.27	0.50
Sharpe ratio	0.01	0.02	−0.11	0.12	0.32	0.28	0.65	1.12
CAPM alpha	0.78*	0.97*	0.54	1.10**	1.58***	1.44***	2.09***	1.55***
	[1.73]	[1.79]	[1.23]	[2.04]	[3.30]	[2.73]	[4.14]	[4.98]
FF3 alpha	0.73***	0.91***	0.47	1.03***	1.54***	1.45***	2.12***	1.65***
	[2.77]	[2.81]	[1.62]	[3.12]	[4.94]	[3.70]	[5.67]	[4.72]
FF4 alpha	0.33	0.39	0.02	0.70**	1.30***	1.17***	1.79***	1.76***
	[1.05]	[1.09]	[0.07]	[2.08]	[3.85]	[2.62]	[5.04]	[4.95]

Table 3: Betting on skewness in beta- and (idiosyncratic) volatility-portfolios

This Table reports results for unconditional portfolio double-sorts. At the end of every month, we sort firms into equally-weighted quintile portfolios based on their CAPM betao (Panel A), idiosyncratic volatility relative to the CAPM (Panel B), idiosyncratic volatility relative to the Fama French three factor model (Panel C), and ex-ante variance (Panel D). Portfolios P_1 and P_5 contain firms with highest and lowest beta/volatility, respectively Independent of the beta/volatility sorts, we also firms into quintile portfolios based on their ex-ante skewness. In each beta/volatility portfolio, we compute the returns of buying high skew and selling low skew stocks and the last column reports the high-minus-low (HL) differential $P_1 - P_5$. We report raw excess returns as well as alphas of CAPM-, Fama-French three-, and four-factor regressions. Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by citetandrews91. The sample period is January 1996 to August 2014.

Panel A. Portfolios sorted by CAPM Beta

	P_1	P_2	P_3	P_4	P_5	HL
Excess return	1.93***	1.09***	1.19***	1.13***	0.89***	1.04***
	[4.53]	[3.54]	[4.44]	[4.13]	[3.87]	[2.73]
Std deviation	6.16	5.10	4.04	3.54	2.68	5.87
Skewness	2.58	1.64	1.43	1.95	0.51	1.41
Sharpe ratio	1.09	0.74	1.02	1.11	1.15	0.62
CAPM alpha	1.66***	0.86***	1.00***	0.99***	0.79***	0.87**
	[4.25]	[2.94]	[3.86]	[3.41]	[3.00]	[2.32]
FF3 alpha	1.62***	0.93***	1.04***	0.91***	0.78***	0.84**
	[4.31]	[3.39]	[5.11]	[3.41]	[3.19]	[2.02]
FF4 alpha	1.99***	1.10***	1.19***	1.08***	0.84***	1.15**
	[4.82]	[4.04]	[4.47]	[4.34]	[3.71]	[2.50]

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Table 3 *(continued)*

Panel B. Portfolios sorted by CAPM idiosyncratic volatility

	P_1	P_2	P_3	P_4	P_5	HL
Excess return	2.16***	1.38***	1.37***	0.78***	0.51***	1.65***
	[6.54]	[5.70]	[4.90]	[4.73]	[4.22]	[4.55]
Std deviation	5.71	3.96	3.15	2.22	1.56	5.73
Skewness	1.55	2.20	1.93	0.77	0.87	0.92
Sharpe ratio	1.31	1.21	1.50	1.22	1.12	1.00
CAPM alpha	1.90***	1.27***	1.32***	0.78***	0.52***	1.38***
	[6.02]	[5.59]	[4.76]	[5.02]	[4.38]	[4.22]
FF3 alpha	1.91***	1.34***	1.27***	0.74***	0.49***	1.41***
	[5.79]	[5.50]	[4.95]	[4.75]	[4.18]	[4.13]
FF4 alpha	2.12***	1.55***	1.38***	0.80***	0.53***	1.58***
	[6.75]	[5.22]	[4.35]	[4.85]	[4.24]	[5.12]

Panel C. Portfolios sorted by FF3 idiosyncratic volatility

	P_1	P_2	P_3	P_4	P_5	HL
Excess return	1.78***	1.39***	1.27***	0.98***	0.58***	1.20***
	[4.79]	[5.10]	[5.58]	[5.40]	[3.72]	[3.25]
Std deviation	5.63	4.08	3.22	2.81	1.84	5.45
Skewness	0.99	1.79	0.58	1.55	0.88	0.38
Sharpe ratio	1.10	1.18	1.37	1.21	1.09	0.77
CAPM alpha	1.46***	1.26***	1.14***	0.91***	0.55***	0.91***
	[4.66]	[4.95]	[4.86]	[4.87]	[3.57]	[2.78]
FF3 alpha	1.54***	1.30***	1.11***	0.89***	0.50***	1.04***
	[5.04]	[4.97]	[5.10]	[5.11]	[3.48]	[3.41]
FF4 alpha	1.78***	1.48***	1.20***	1.01***	0.57***	1.21***
	[5.30]	[5.24]	[5.20]	[5.33]	[3.53]	[3.90]

Panel D. Portfolios sorted by ex-ante variance

	P_1	P_2	P_3	P_4	P_5	HL
Excess return	2.38***	1.40***	1.05***	0.71***	0.54***	1.85***
	[6.45]	[5.42]	[4.61]	[4.24]	[3.48]	[5.80]
Std deviation	5.62	3.76	2.72	2.39	1.64	5.72
Skewness	0.92	0.49	0.38	1.33	0.75	0.50
Sharpe ratio	1.47	1.29	1.33	1.03	1.14	1.12
CAPM alpha	2.14***	1.35***	1.10***	0.74***	0.59***	1.55***
	[5.82]	[4.48]	[4.81]	[4.62]	[3.94]	[4.98]
FF3 alpha	2.22***	1.31***	1.06***	0.75***	0.57***	1.65***
	[5.89]	[4.04]	[5.01]	[4.61]	[3.74]	[4.72]
FF4 alpha	2.38***	1.42***	1.11***	0.84***	0.62***	1.76***
	[6.22]	[5.01]	[4.87]	[5.31]	[4.38]	[4.95]

Table 4: Leverage, skewness, and equity returns

This Table summarizes results for leverage differentials across skew-sorted portfolios in Panel A and equity returns of leverage-sorted portfolios in Panels B and C. For Panel A, we sort firms into quintile- or decile-portfolios based on their ex-ante skewness at the end of every month and compute differences in book leverage and market leverage of firms with high skewness minus that of firms with low skewness (in percentage points). For Panels B and C, we sort firms into quintile- or decile-portfolios based on their book leverage or market leverage at the end of every month. We then compute the equally-weighted (Panel B) and value-weighted (Panel C) returns to buying high and selling low leverage firms and estimate the Fama-French four-factor alpha. We then augment the FF4-regression by a skew-factor (the high-minus-low returns of skew-sorted portfolios) and SKEW beta reports the regression coefficient for this factor. SKEW alpha reports the alpha of the skew-augmented FF4 regression. Equity returns and alphas are monthly (in percentage points). Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by Andrews (1991). The data is sampled at a monthly frequency over the period January 1996 to August 2014.

Panel A. Leverage differentials in skew-sorted portfolios

	Book Leverage		Market Leverage	
	5 Skew-Port.	10 Skew-Port.	5 Skew-Port.	10 Skew-Port.
Leverage Differentials	−3.83***	−4.26***	−4.46***	−4.99***
	[-10.22]	[-10.41]	[-6.06]	[-6.89]

Panel B. Equity returns of portfolios sorted by leverage: Equally-weighted

	Book Leverage		Market Leverage	
	5 Blev-Port.	10 Blev-Port.	5 Mlev-Port.	10 Mlev-Port.
Excess return	−0.05	−0.14	0.08	0.01
	[-0.17]	[-0.43]	[0.21]	[0.02]
FF4 alpha	−0.17	−0.29	−0.17	−0.32
	[-0.87]	[-1.23]	[-0.92]	[-1.60]
SKEW beta	−0.32***	−0.24***	−0.37***	−0.34***
	[-4.14]	[-2.74]	[-4.60]	[-3.23]
SKEW FF4 alpha	0.09	−0.10	0.13	−0.04
	[0.54]	[-0.45]	[0.81]	[-0.21]

Panel C. Equity returns of portfolios sorted by leverage: Value-weighted

	Book Leverage		Market Leverage	
	5 Blev-Port.	10 Blev-Port.	5 Mlev-Port.	10 Mlev-Port.
Excess return	−0.33	−0.43	−0.21	−0.32
	[-0.92]	[-1.14]	[-0.48]	[-0.66]
FF4 alpha	−0.58**	−0.73***	−0.60***	−0.78***
	[-2.51]	[-2.98]	[-3.19]	[-2.94]
SKEW beta	−0.49***	−0.35***	−0.37***	−0.43***
	[-4.89]	[-3.14]	[-3.64]	[-4.01]
SKEW FF4 alpha	−0.18	−0.44*	−0.29	−0.43
	[-0.77]	[-1.74]	[-1.49]	[-1.46]

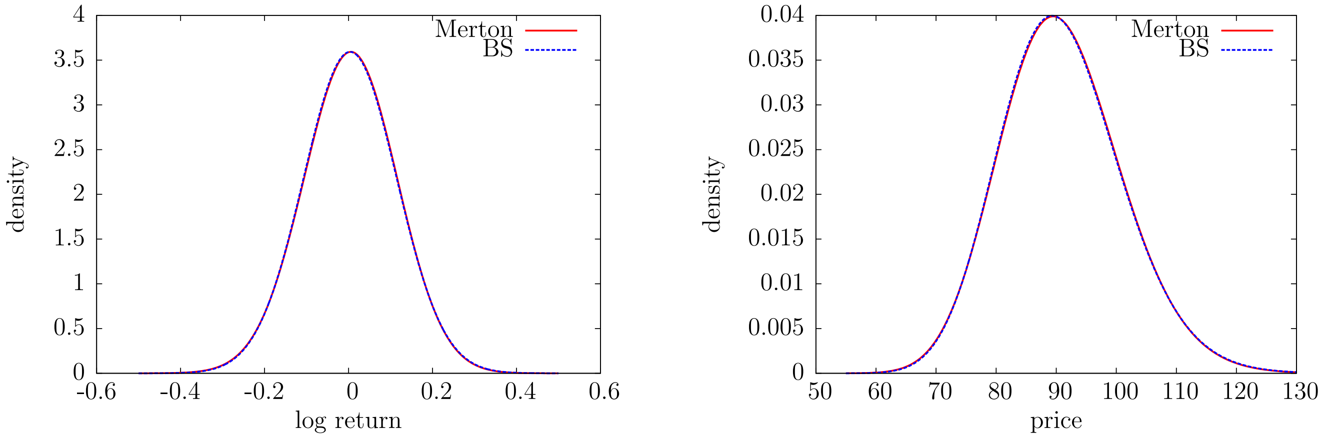
Table 5: Betting against $MAX5$ in skew-portfolios

This Table reports equity excess returns of betting against $MAX5$, defined as the average of a firm's five highest daily returns over the past month. We compute the returns of buying low and selling high $MAX5$ stocks. The first two columns report excess returns of betting against $MAX5$ using quintile and decile portfolios, respectively. The remaining columns report results from unconditional portfolio double-sorts. We sort firms into equally-weighted quintile portfolios based on their ex-ante skewness, where Skew-P_1 and Skew-P_5 contain firms with highest and lowest ex-ante skewness, respectively. Independent of the skew-sorts, we also sort firms into equally-weighted quintile portfolios based on $MAX5$. For every skew portfolio, we compute the returns of betting against $MAX5$. The last column reports the $P_5 - P_1$ differential. We report raw excess returns and alphas of CAPM-, Fama-French three-, and four-factor regressions. Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by Andrews (1991). The data covers 4,967 US firms, is sampled at a monthly frequency over the period January 1996 to August 2014, and contains a total of 400,449 observations.

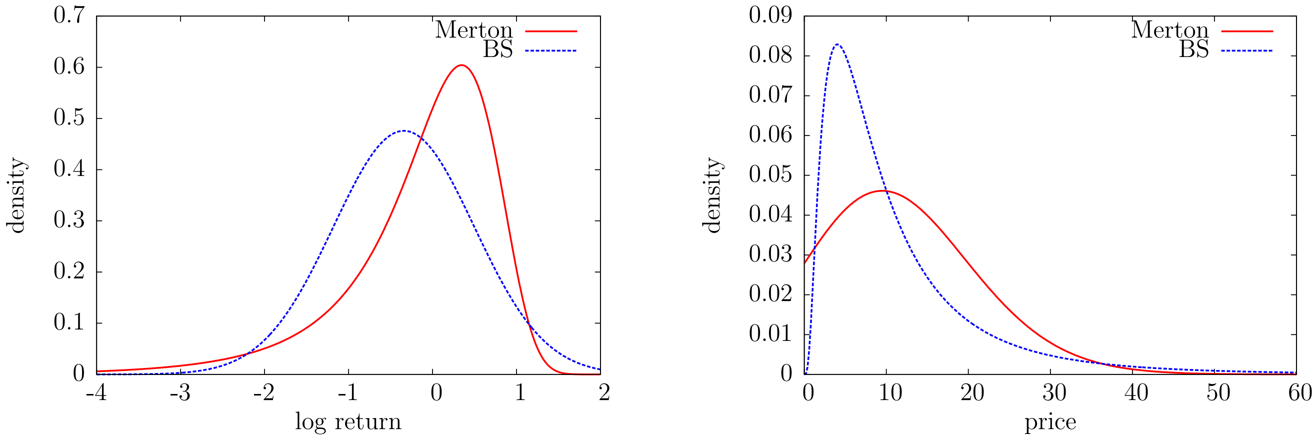
	Betting against Risk		Betting against Risk in Skew Portfolios					
	5 Port.	10 Port	Skew-P_1	Skew-P_2	Skew-P_3	Skew-P_4	Skew-P_5	$P_5 - P_1$
Excess return	0.39	0.45	0.32	0.73	0.53	0.86	1.06**	0.75**
	[0.76]	[0.75]	[0.54]	[1.34]	[1.08]	[1.61]	[2.30]	[2.29]
Std deviation	8.00	9.47	8.69	8.19	7.42	7.67	6.76	4.68
Skewness	−0.83	−0.97	−0.54	−1.14	−0.52	−1.00	−0.29	0.68
Sharpe ratio	0.17	0.17	0.13	0.31	0.25	0.39	0.55	0.55
CAPM alpha	1.03***	1.20**	1.03**	1.30***	1.09***	1.43***	1.57***	0.53*
	[2.63]	[2.56]	[2.31]	[2.70]	[3.11]	[3.22]	[3.74]	[1.80]
FF3 alpha	0.97***	1.17***	0.98***	1.21***	1.02***	1.39***	1.55***	0.57**
	[4.22]	[4.38]	[3.48]	[4.02]	[3.53]	[4.38]	[5.77]	[2.03]
FF4 alpha	0.73**	0.86***	0.70**	1.07***	0.88***	1.25***	1.38***	0.68**
	[2.49]	[2.90]	[2.46]	[3.25]	[3.07]	[3.57]	[4.98]	[2.15]

Figure 1: $\mathbb{Q}$-densities of Merton model-implied equity prices and returns

(a) Low leverage



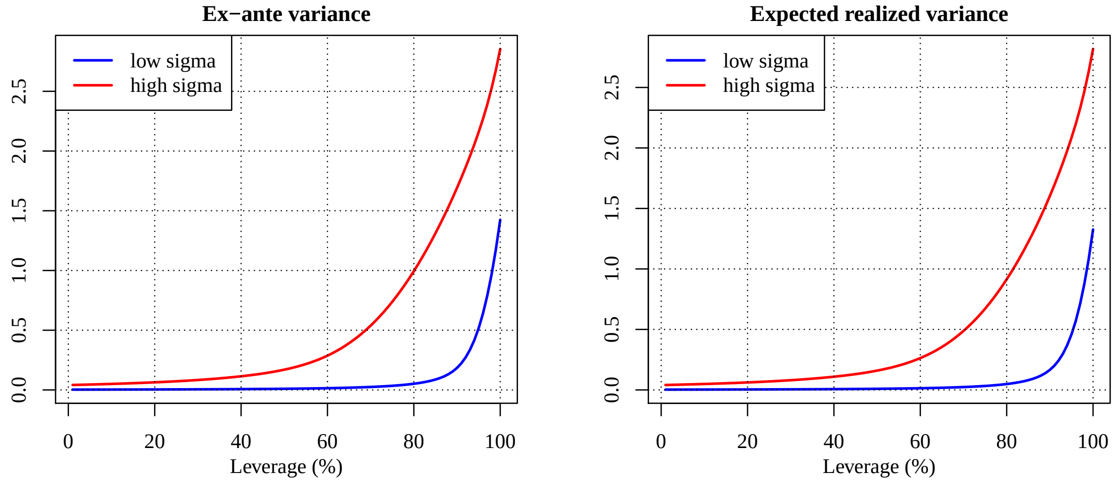
(b) Low leverage



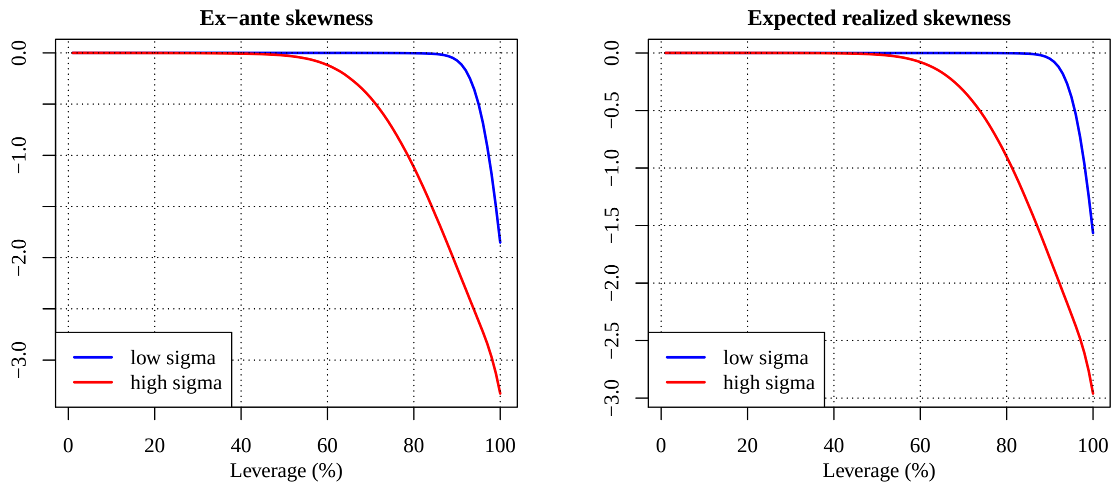
The figure plots Merton-implied and Black-Scholes-implied densities of equity log returns and prices. We present two examples: a low credit risk firm in Panel (a) and a high credit risk firm in Panel (b), which only differ by the face value of debt issued which is $D = 10$ and $D = 90$, respectively. The remaining parameters are time to maturity $T = 1$, value of assets today $V_0 = 100$, asset volatility $\sigma = 0.1$ and the risk-free rate $r = 0.01$. Densities are computed using the $\mathbb{Q}$-distribution of equity implied by Merton's model, and a correspondingly parameterized Black-Scholes (BS) model. The Merton density of the price is obtained by first computing the distribution function of equity via $\mathbb{E}_0^{\mathbb{Q}}\left[\mathbb{1}_{\{\max(V_t - D, 0) \leq x\}}\right]$, and taking the partial derivative with respect to x. The Merton density of the log return is obtained by the change of variables $\log(E_t/E_0)$, where E_s is the Merton-implied value of equity at time s. For the Black-Scholes density we first invert an at-the-forward Merton-implied option on E_t for BS implied volatility IV, and then use the Normal, resp. Lognormal density functions using E_0, r, T and IV.

Figure 2: Ex-ante and realized variance and skewness

(a) Variance under the $\mathbb{Q}$- and $\mathbb{P}$-measure



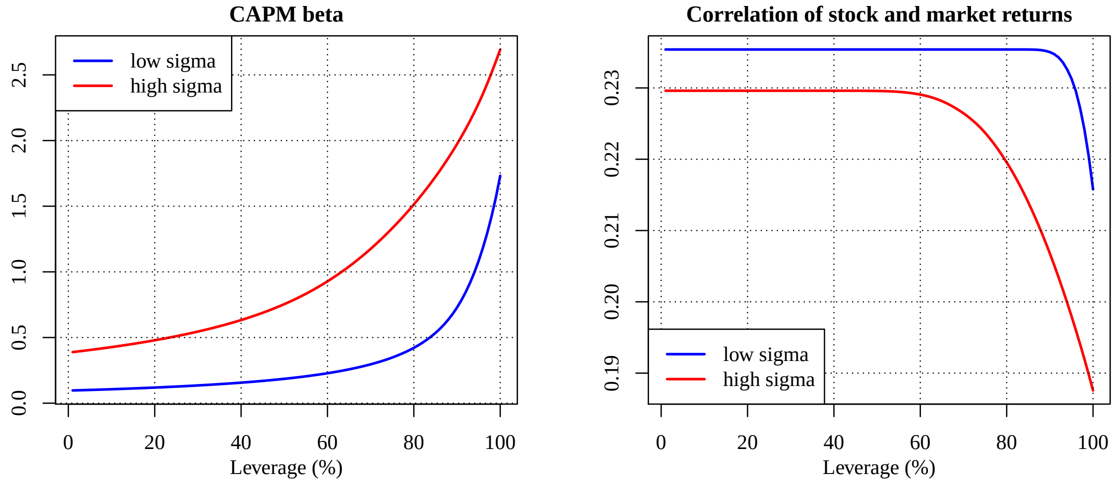
(b) Skewness under the $\mathbb{Q}$- and $\mathbb{P}$-measure



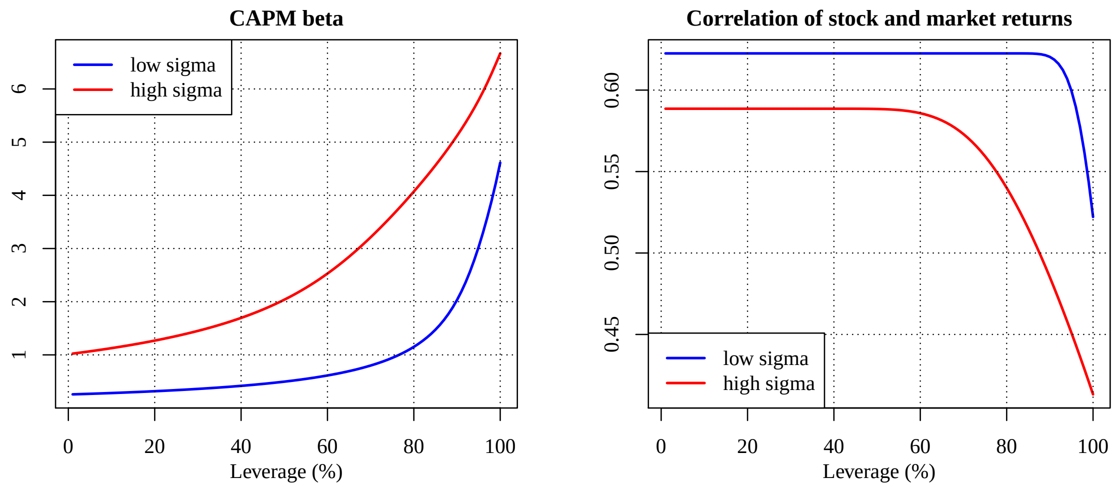
This Figure shows ex-ante moments (under the $\mathbb{Q}$-measure, left column) and expected realized moments (under the $\mathbb{P}$-measure, right column) of a firm's equity return distribution depending on the firm's credit risk. Panel (a) presents results for variance, Panel (b) presents results for skewness. In each plot, we consider a low asset volatility scenario ($\sigma_i = 5\%$, in blue) and a high asset volatility scenario ($\sigma_i = 20\%$, in red) with an expected asset return $\mu = 3\%$. The correlation of the firm's assets with the market $\rho = 30\%$. The market risk premium is 5% p.a., resulting from the forward market price dynamics in Equation (1) being parametrized by $\xi = -0.85, \gamma = 2$, and for the stochastic market variance $\nu_0 = 0.025, \nu_1 = -1$, and volatility $\vartheta = 0.4$. All quantities are computed for a time horizon of 1 year, by simulating daily increments for the discretized stochastic differential equations of the market dynamics in Equation (1) and the asset value process in Equation (9) along 500,000 sample paths.

Figure 3: Model-implied CAPM betas

(a) Low correlation with the market



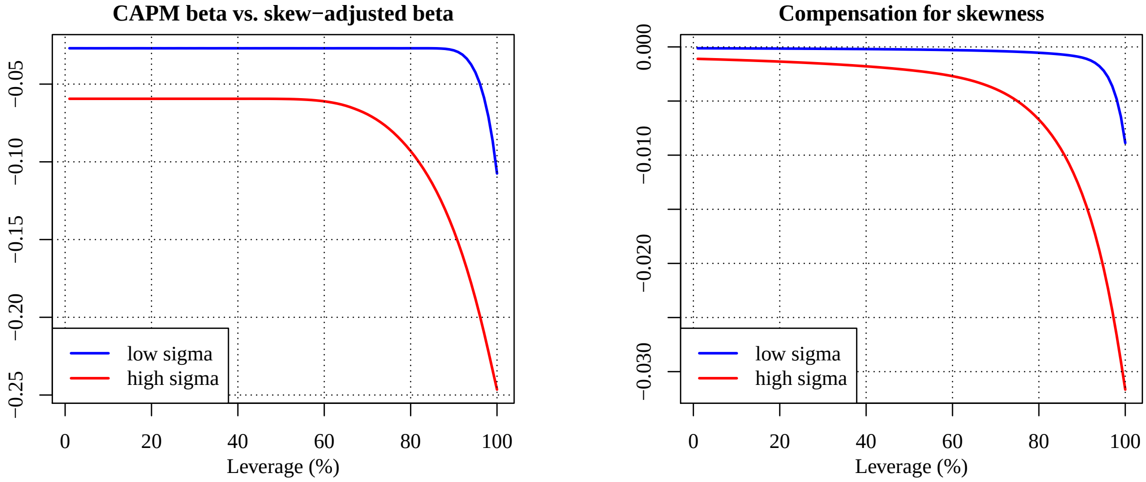
(b) High correlation with the market



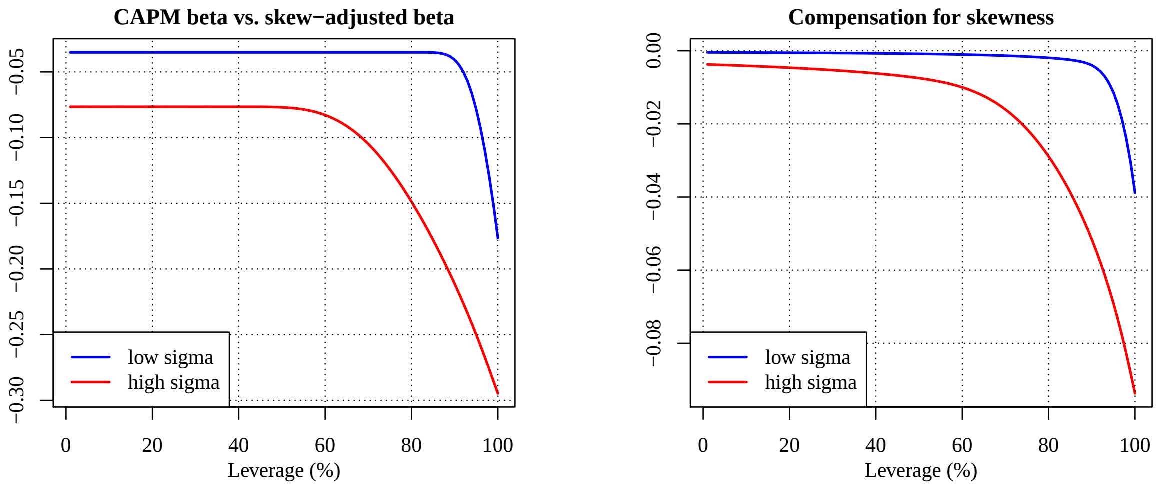
This Figure shows CAPM betas (left column) and correlations of stock returns with market returns (right column). In each plot, we consider a low asset volatility scenario ($\sigma_i = 5\%$, in blue) and a high asset volatility scenario ($\sigma_i = 20\%$, in red) with an expected asset return $\mu = 3\%$. In Panel (a), the firm has a low asset correlation with the market ($\rho_i = 30\%$), Panel (b) the firm has a high asset correlation with the market ($\rho_i = 80\%$). The market risk premium is 5% p.a., resulting from the forward market price dynamics in Equation (1) being parametrized by $\xi = -0.85, \gamma = 2$, and for the stochastic market variance $\nu_0 = 0.025, \nu_1 = -1$, and volatility $\vartheta = 0.4$. All quantities are computed for a time horizon of 1 year, by simulating daily increments for the discretized stochastic differential equations of the market dynamics in Equation (1) and the asset value process in Equation (9) along 500,000 sample paths.

Figure 4: Impact of skewness on expected equity returns

(a) Low correlation with the market



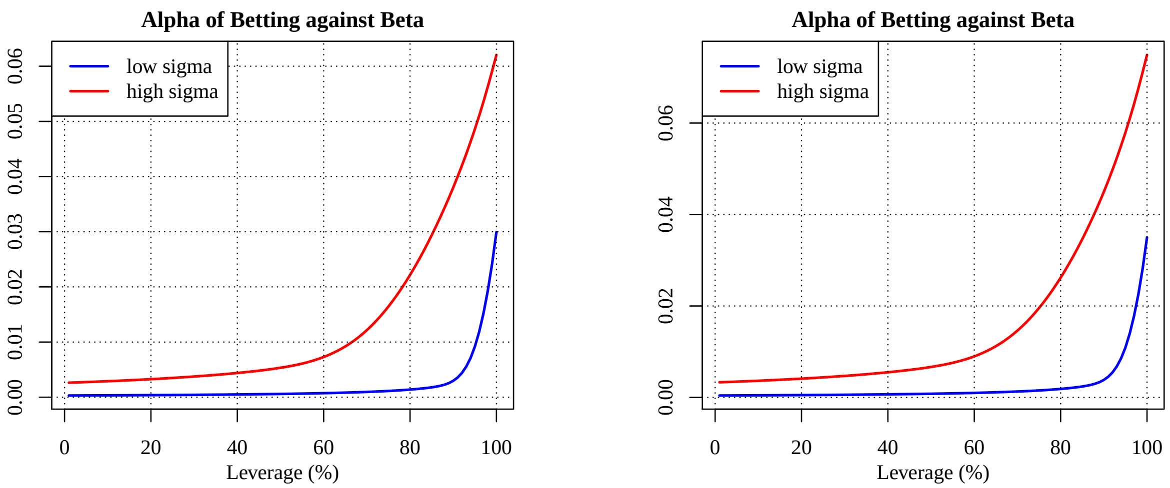
(b) High correlation with the market



This Figure illustrates the impact of skewness on expected equity returns. The left column plots deviations of the CAPM beta (β_i^{CAPM}) from the skew-adjusted beta ($\beta_i^{skew-adj}$) as $\beta_i^{skew-adj}/\beta_i^{CAPM} - 1$. The right column plots the compensation for skewness by computing the skew component of expected equity returns as $\mathbb{E}^{\mathbb{P}}\left[R_i^{skew}\right] = (\beta_i^{skew-adj} - \beta_i^{CAPM}) \times \mathbb{E}^{\mathbb{P}}\left[R\right]$, where $\mathbb{E}^{\mathbb{P}}\left[R\right]$ is the expected excess return on the market. In each plot, we consider a low asset volatility scenario ($\sigma_i = 5\%$, in blue) and a high asset volatility scenario ($\sigma_i = 20\%$, in red) with an expected asset return $\mu = 3\%$. In Panel (a), the firm has a low asset correlation with the market ($\rho_i = 30\%$), Panel (b) the firm has a high asset correlation with the market ($\rho_i = 80\%$. The market risk premium is 5% p.a., resulting from the forward market price dynamics in Equation (1) being parametrized by $\xi = -0.85, \gamma = 2$, and for the stochastic market variance $\nu_0 = 0.025, \nu_1 = -1$, and volatility $\vartheta = 0.4$. All quantities are computed for a time horizon of 1 year, by simulating daily increments for the discretized stochastic differential equations of the market dynamics in Equation (1) and the asset value process in Equation (9) along 500,000 sample paths.

Figure 5: Betting against beta

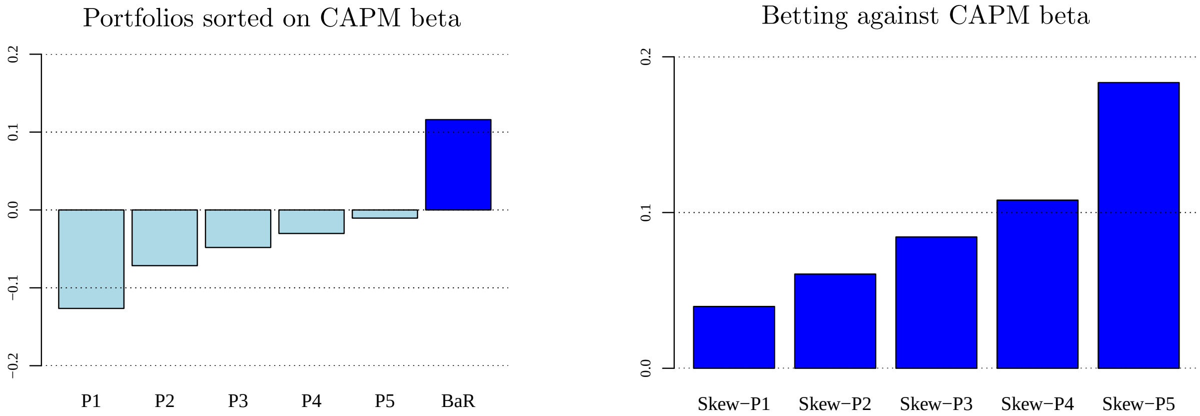
(a) High vs low correlation　　(b) High vs very low correlation



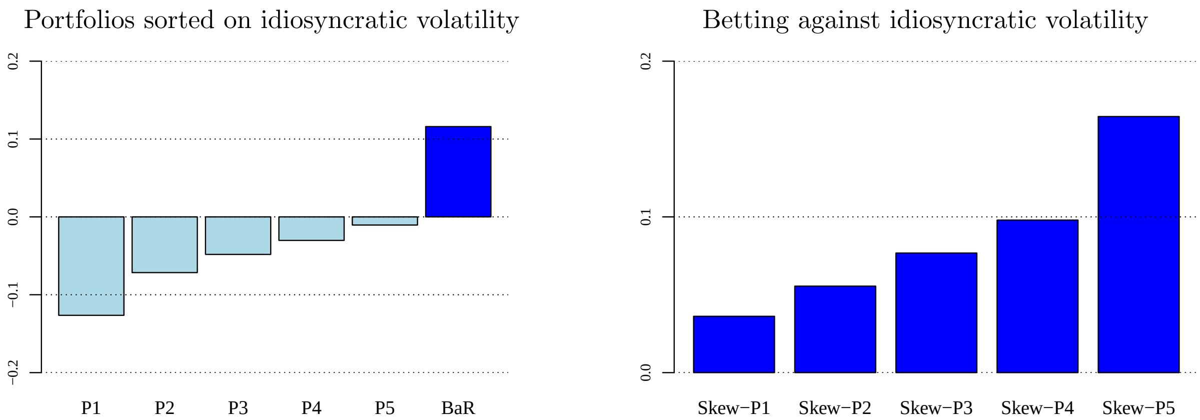
This Figure illustrates the alphas of betting against beta (BaB), i.e. the strategy that buys stocks with low CAPM beta and sells stocks with high CAPM beta. We measure alphas as the expected excess return beyond compensation for market covariance risk, i.e. by $\mathbb{E}^{\mathbb{P}}\left[R_i^{skew}\right] = (\beta_i^{skew-adj} - \beta_i^{CAPM}) \times \mathbb{E}^{\mathbb{P}}[R]$ where β_i^{CAPM} is the CAPM beta, $\beta_i^{skew-adj}$ is the skew-adjusted beta, and $\mathbb{E}^{\mathbb{P}}[R]$ is the expected excess return on the market. In each plot, we consider a low asset volatility scenario ($\sigma_i = 5\%$, in blue) and a high asset volatility scenario ($\sigma_i = 20\%$, in red) with an expected asset return $\mu = 3\%$. In Panel (a) high (low) beta stocks are stocks whose assets are correlated with the market with $\rho_i = 80\%$ ($\rho_i = 30\%$); in Panel (b), we use stocks with high correlation of $\rho_i = 80\%$ and very low correlation of $\rho_i = 5\%$. The market risk premium is 5% p.a., resulting from the forward market price dynamics in Equation (1) being parametrized by $\xi = -0.85, \gamma = 2$, and for the stochastic market variance $\nu_0 = 0.025, \nu_1 = -1$, and volatility $\vartheta = 0.4$. All quantities are computed for a time horizon of 1 year, by simulating daily increments for the discretized stochastic differential equations of the market dynamics in Equation (1) and the asset value process in Equation (9) along 500,000 sample paths.

Figure 6: Model simulation results

(a) Simulation results for CAPM betas

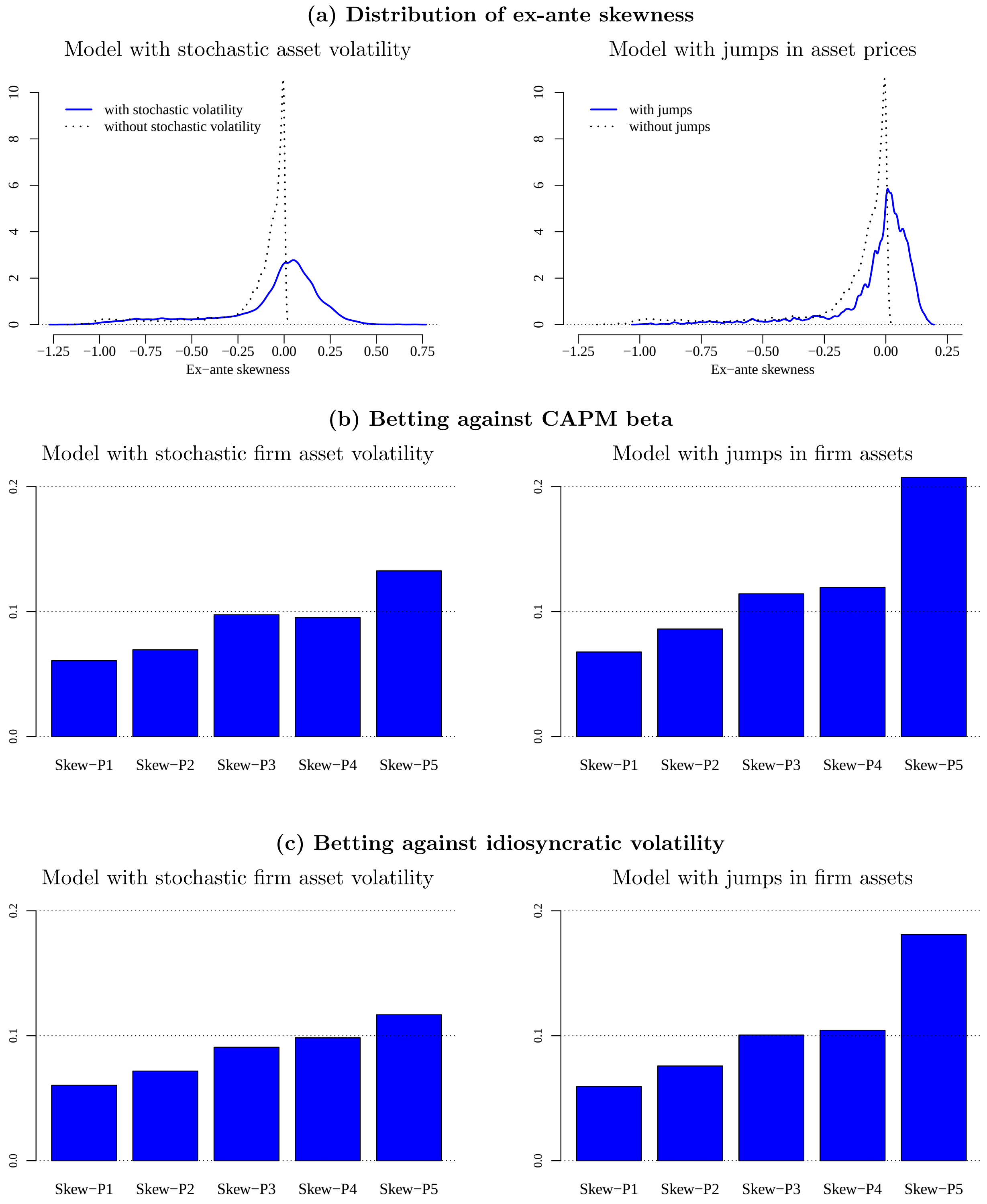


(b) Simulation results for idiosyncratic volatility



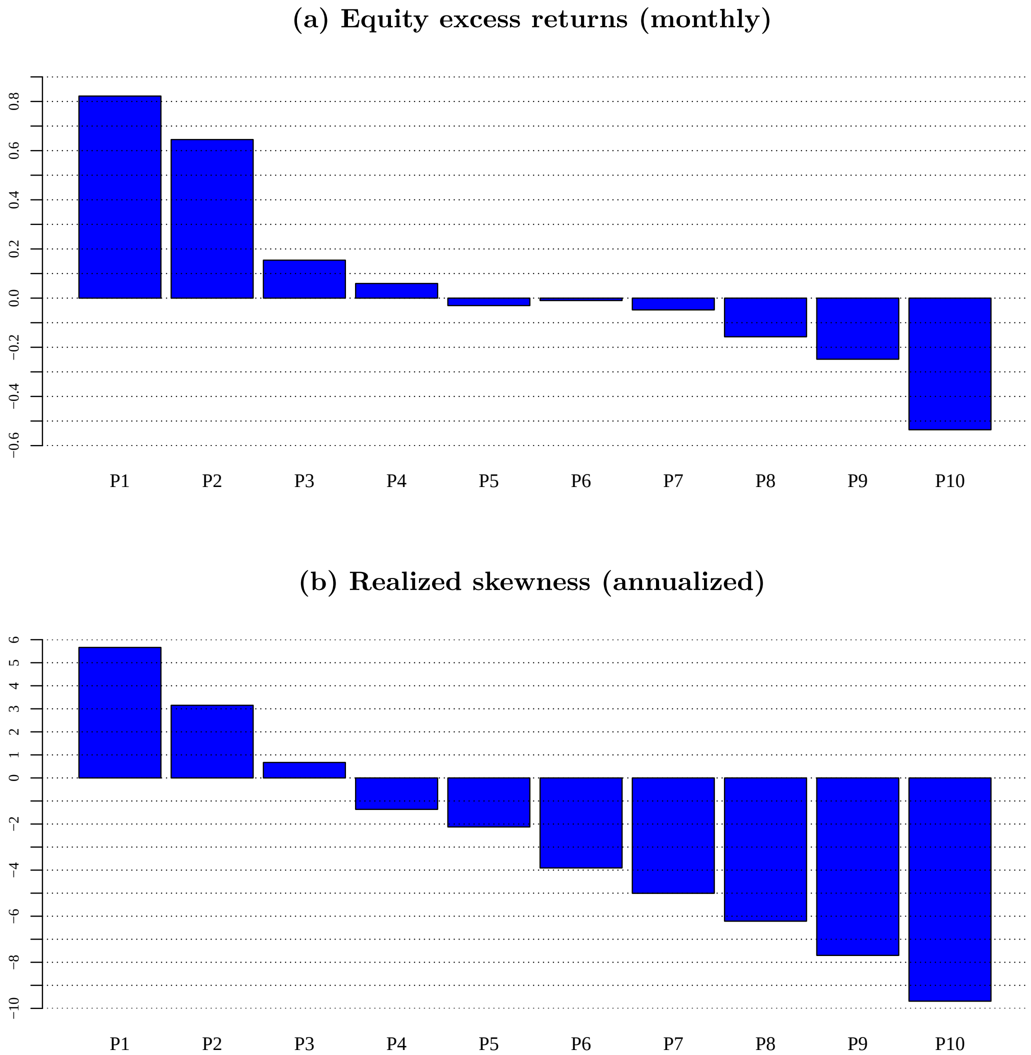
Using the structural model described in Section 2, we simulate a cross-section of 2,000 firms over a time-series of 240 months. At the end of every month, we sort firms into quintile portfolios based on their CAPM beta (Panel a) or based on their idiosyncratic volatility relative to the CAPM (Panel b). Portfolios P_1 and P_5 contain firms with highest (lowest) risk, respectively. For every portfolio as well as for the strategy of buying low risk and selling high risk stocks (betting against risk, BaR), we compute equity excess returns and report model-implied CAPM alphas, i.e. equity returns in excess of compensation for market covariance risk, in the left column. In the right column, we report alphas of the BaR strategies when we control for firms' ex-ante skewness. At the end of every month, we assign firms to skew-quintiles with portfolio Skew-P_1 and Skew-P_5 containing firms with highest and lowest ex-ante skewness, respectively. For every skew portfolio, we compute the model- implied alphas of betting against beta/volatility. For details on the simulation procedure see Appendix A.

Figure 7: Simulation results for models with stochastic volatility or jumps in firm assets



Using the baseline structural model and its extensions to account for stochastic asset volatility or jumps in asset prices (described in Section 2), we simulate cross-sections of 2,000 firms over time-series of 240 months. Panel (a) presents the sample distributions of ex-ante skewness. Panels (b) and (c) report alphas of betting against beta and volatility strategies when we control for firms' ex-ante skewness. At the end of every month, we assign firms to skew-quintiles with portfolio Skew-P_1 and Skew-P_5 containing firms with highest and lowest ex-ante skewness, respectively. For every skew portfolio, we compute the alphas of betting against CAPM beta (Panel b) and idiosyncratic volatility (Panel c). For details on the simulation procedure see Appendix A.

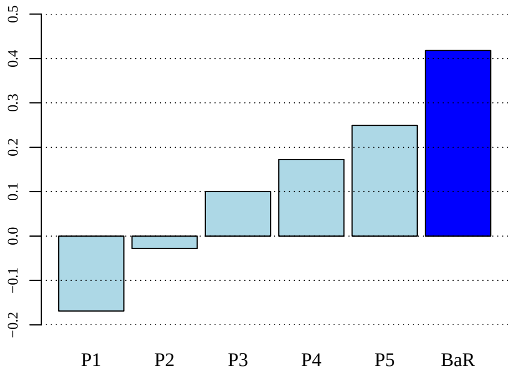
Figure 8: Ex-ante skewness and the distribution of future equity returns



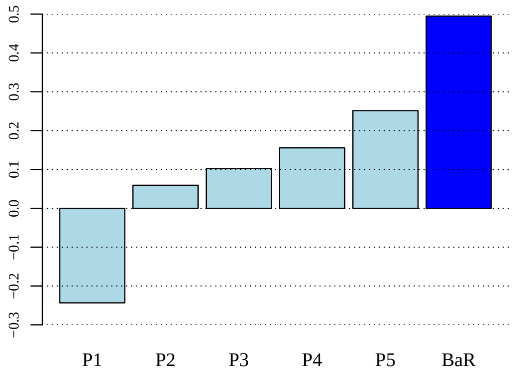
At the end of every month, we sort firms into equally-weighted decile portfolios based on their ex-ante skewness. Portfolio P_1 (P_{10}) contains firms with highest (lowest) ex-ante skewness. For every portfolio, we compute equity excess returns (a) and realized skewness (b). Values reported are alphas of Fama-French four-factor regressions. The sample period is January 1996 to August 2014.

Figure 9: Equity returns of CAPM beta- and volatility-sorted portfolios

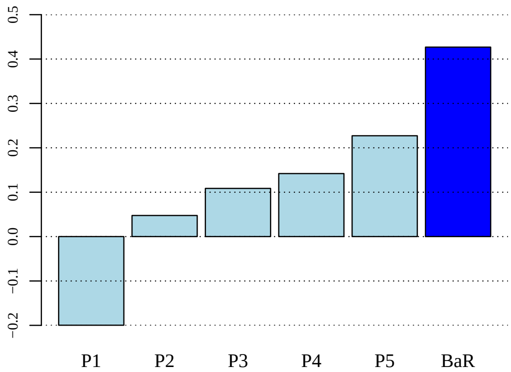
(a) Portfolios sorted on CAPM Beta



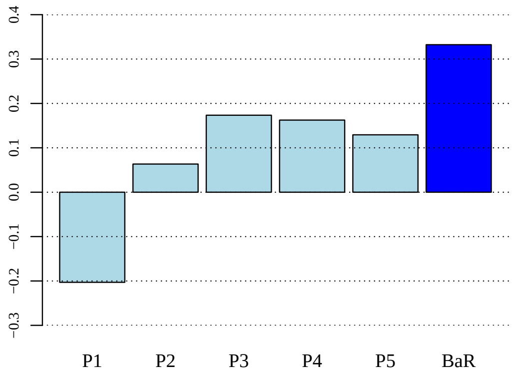
(b) Portfolios sorted on CAPM Idio. Vol.



(c) Portfolios sorted on FF3 Idio Vola



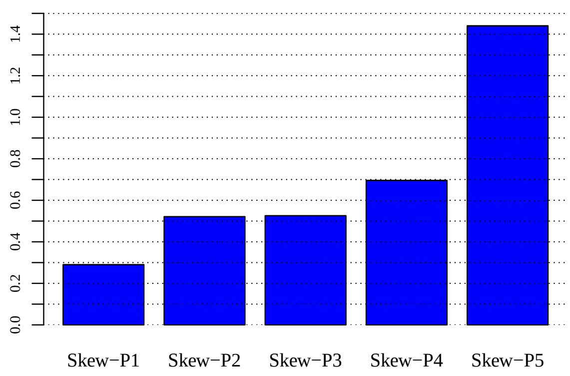
(d) Portfolios sorted on Variance



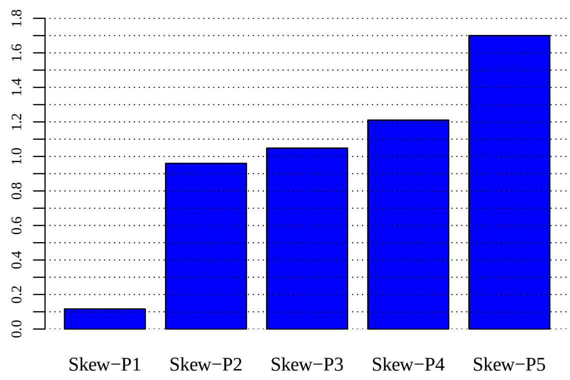
At the end of every month, we sort firms into equally-weighted quintile portfolios based on their CAPM beta (a), idiosyncratic volatility relative to the CAPM (b), idiosyncratic volatility relative to the Fama-French three-factor model (c), and ex-ante variance (d). Portfolio P_1 (P_5) contains firms with highest (lowest) risk, respectively. For every portfolio as well as for the strategy of buying low risk and selling high risk stocks (betting against risk, BaR), we compute equity excess returns and report alphas of Fama-French four-factor regressions. The sample period is January 1996 to August 2014.

Figure 10: Betting against risk in skew portfolios

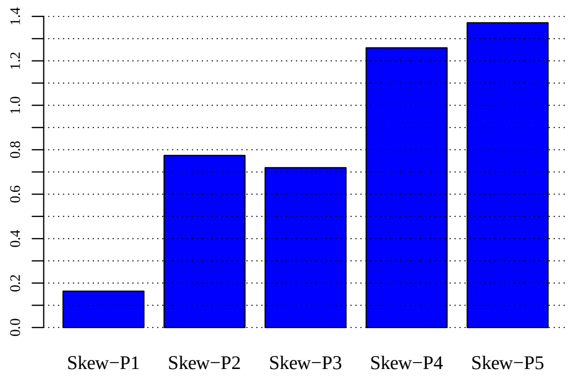
(a) Betting against CAPM Beta



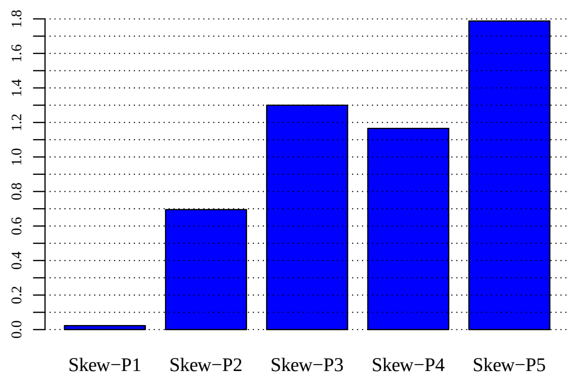
(b) Betting against CAPM Idio. Vol.



(c) Betting against FF3 Idio Vola



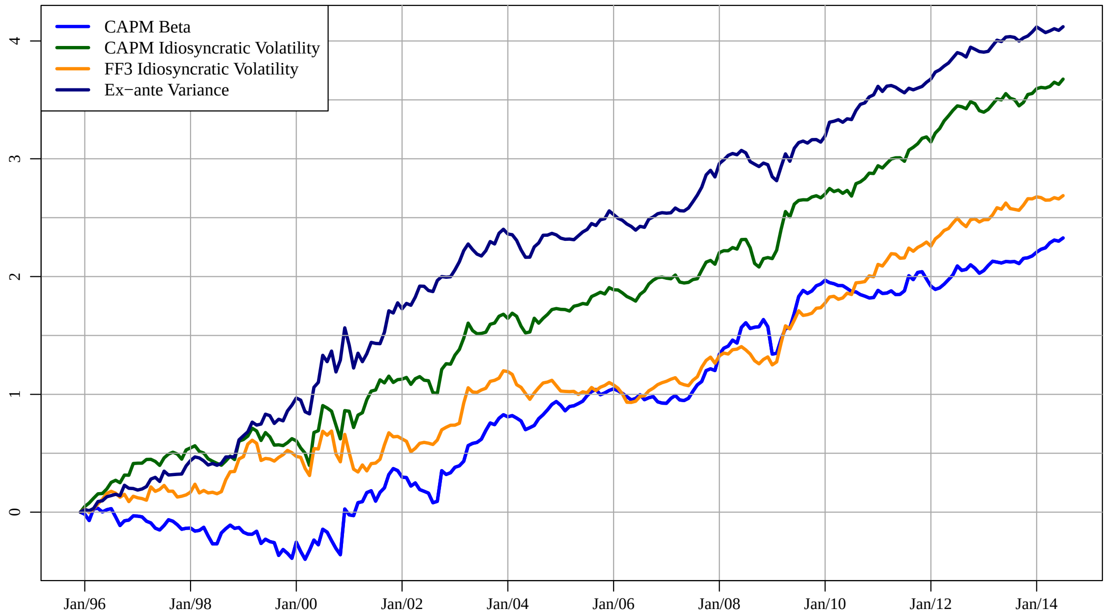
(d) Betting against ex-ante variance



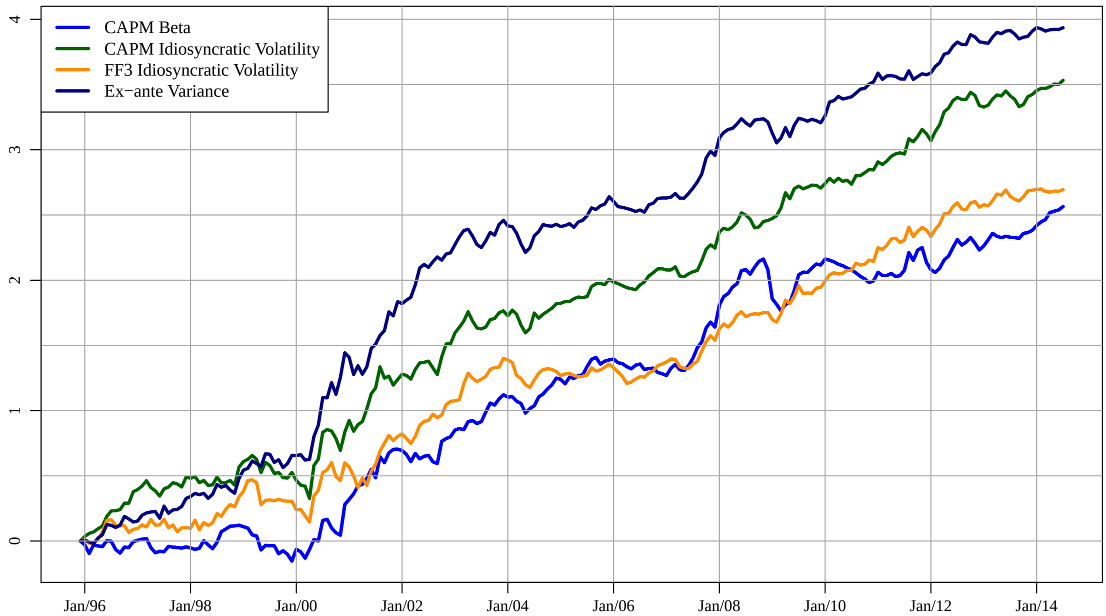
At the end of every month, we sort firms into equally-weighted quintile portfolios based on their ex-ante skewness. Portfolios Skew-P_1 and Skew-P_5 contain firms with highest and lowest ex-ante skewness, respectively. Independent of the skew-sorts, we also sort firms into equally-weighted quintile portfolios based on either their CAPM beta, idiosyncratic volatility, or their ex-ante variance. For every skew portfolio, we compute the returns of betting against beta/volatility. In Panel (a), we compute the returns of buying low and selling high CAPM beta stocks (betting against beta). Similarly we compute the returns, to buying low risk and selling high risk stocks using idiosyncratic volatility relative to the CAPM (Panel b), idiosyncratic volatility relative to the Fama French three factor model (Panel c), and ex-ante variance (Panel d) as risk measures. Values reported are alphas of Fama-French four-factor regressions. The sample period is January 1996 to August 2014.

Figure 11: Cumulative returns of betting against beta/volatility in low vs high skew stocks

(a) Equity excess returns



(b) Four-factor alphas



This figure plots the cumulative returns and four-factor alphas of betting against beta/volatility in low skew portfolios (Skew-P_5) in excess of betting against beta/volatility in high skew portfolios (Skew-P_1), resulting from unconditional portfolio double-sorts. At the end of every month, we sort firms into equally-weighted quintile portfolios based on their ex-ante skewness. Independent of the skew-sorts, we also sort firms into equally-weighted quintile portfolios based on either their CAPM beta, idiosyncratic volatility relative to the CAPM and relative to the Fama French three factor model, and ex-ante variance. For each of these beta/volatility measures, we compute the monthly Skew-P_5-Skew-P_1 excess returns and illustrate their accumulation over the sample period from January 1996 to August 2014.

Internet Appendix for

Low Risk Anomalies?

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(not for publication)

February 2016

In the paper, we discuss various robustness checks (see Section 5) but do not report results due to space reasons. This Internet Appendix presents the corresponding empirical results in detail. Table IA.1 presents the equity returns of portfolios sorted by coskewness as measured by Harvey and Siddique (2000) and Table IA.2 presents results for unconditional portfolio double sorts to provide additional evidence that the prevalence of low risk anomalies is related to coskewness. Tables IA.3 and IA.4 present results for skew-sorted and skew-double sorted portfolios when measure all option-implied quantities on the business day before firms are assigned to portfolios.

Below, we present several additional results to show that our findings are robust to variations in the portfolio sort procedure.

Robustness: Number of portfolios. The unconditional double sort procedure employed in the core analysis uses a total of 25 ($N \times N$, with $N = 5$) portfolios. If the relation between skewness and low risk anomalies is characterized as argued in this paper, we should find that the differential returns of betting against beta/volatility in low skew compared to high skew portfolios increases as we define the portfolio grid more finely. The first three columns of Table IA.5 provide supporting evidence for choosing $N = 7$ and $N = 10$.

Robustness: Value-weighted and rank-weighted portfolios. We now check whether our results are robust to different portfolio weighting schemes and present these results also in Table IA.5. While the return differential of betting against beta/volatility in low relative to high skew portfolios is almost always positive with alphas mostly similar to those of equally-weighted portfolios, there is more variation in levels of significance compared to using equally-weighted portfolios. Using rank-weighted portfolios, all skew related return differentials in betting against beta/volatility are highly significant with alphas similar or slightly higher compared to equally-weighted portfolios.

Robustness: Conditional double sorts. While unconditional double sorts are conceptually more suitable to test the model predictions, the advantage of conducting conditional double sorts is that all $N \times N$ sequentially-sorted portfolios contain the same number of firms. In such a sequential procedure, we first sort firms into quintile portfolios based on their ex-ante skewness and, subsequently, we sort firms within each skew portfolio into quintile portfolios according to their beta or volatility. The first three columns of Table IA.6 show that all return differentials of betting against beta/volatility among low compared to high skew firms are positive but that results are, as to be expected, somewhat less pronounced compared to the independent sorts reported above. We also conduct conditional portfolio sorts where we first sort firms into beta/volatility portfolios and within these portfolios according to their ex-ante skewness. Computing the return differentials of buying high and selling low skew firms among high beta/volatility compared to low beta/volatility firms (which are in the case of sequential sorts not identical to betting against beta/volatility in low compared to high skew portfolios), we also find that all differential returns are positive and that all are significant, except for a few portfolio combinations for CAPM betas.

Table IA.1: Portfolios sorted by coskewness

This Table summarizes firm characteristics and equity returns across skew-portfolios. At the end of every month, we rank firms based on their coskewness (measured as in Harvey and Siddique, 2000) and assign firms to portfolios, with P_1 (P_{10}) containing firms with highest (lowest) coskewness. In Panels A and B, we present the returns of equally-weighted portfolios and value-weighted portfolios, respectively. We report monthly equity returns (in percentage points) for individual portfolios as well as the $P_1 - P_{10}$ differential (HL). We report raw excess returns along with standard deviations and Sharpe ratios (annualized), as well as alphas of CAPM-, Fama-French three-, and four-factor regressions. Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by Andrews (1991). The data covers 4,967 US firms, is sampled at a monthly frequency over the period January 1996 to August 2014, and contains a total of 400,449 observations.

Panel A. Equity returns of portfolios sorted by Coskewness: Equally-weighted

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	HL
Excess return	0.49	0.70	0.85*	0.80*	0.94*	0.85*	0.88*	0.97**	0.90*	0.96*	−0.48**
	[1.14]	[1.63]	[1.93]	[1.76]	[1.94]	[1.75]	[1.92]	[2.02]	[1.87]	[1.83]	[-2.07]
Std deviation	6.45	6.42	6.37	6.25	6.35	6.32	6.25	6.41	6.50	6.77	4.14
Skewness	−0.60	−0.40	−0.43	−0.49	−0.30	−0.25	−0.49	−0.29	−0.48	−0.25	−0.42
Sharpe ratio	0.26	0.38	0.46	0.44	0.51	0.47	0.49	0.52	0.48	0.49	−0.40
CAPM alpha	−0.23	−0.03	0.13	0.08	0.21	0.12	0.15	0.23	0.15	0.19	−0.42*
	[-1.49]	[-0.13]	[0.62]	[0.35]	[0.93]	[0.55]	[0.86]	[0.96]	[0.68]	[0.86]	[-1.73]
FF3 alpha	−0.31*	−0.17	−0.05	−0.11	0.02	−0.05	−0.01	0.04	−0.02	0.04	−0.35
	[-2.03]	[-1.06]	[-0.34]	[-0.78]	[0.16]	[-0.37]	[-0.06]	[0.27]	[-0.20]	[0.26]	[-1.60]
FF4 alpha	−0.11	0.04	0.13	0.02	0.15	0.06	0.09	0.15	0.02	0.09	−0.20
	[-0.87]	[0.29]	[1.06]	[0.19]	[1.25]	[0.48]	[0.84]	[1.07]	[0.21]	[0.55]	[-0.78]

Panel B. Equity returns of portfolios sorted by Coskewness: Value-weighted

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	HL
Excess return	0.15	0.53	0.74**	0.50	0.78**	0.85*	0.59	0.83**	0.80**	0.86**	−0.70**
	[0.34]	[1.36]	[2.13]	[1.31]	[2.00]	[1.94]	[1.58]	[2.20]	[2.24]	[2.13]	[-2.24]
Std deviation	6.39	6.00	5.47	5.33	5.17	5.49	5.18	5.30	4.98	5.81	5.94
Skewness	−0.79	−0.02	−0.11	−0.75	−0.59	0.42	−0.75	−0.20	−0.31	0.05	−0.26
Sharpe ratio	0.08	0.31	0.47	0.33	0.52	0.54	0.40	0.54	0.55	0.51	−0.41
CAPM alpha	−0.52**	−0.13	0.12	−0.12	0.18	0.23*	−0.01	0.24	0.26	0.25	−0.77**
	[-2.50]	[-1.04]	[0.75]	[-0.73]	[0.99]	[1.78]	[-0.10]	[1.30]	[1.40]	[1.26]	[-2.22]
FF3 alpha	−0.42**	−0.10	0.12	−0.19	0.12	0.14	−0.08	0.14	0.15	0.16	−0.58**
	[-2.39]	[-0.58]	[0.74]	[-1.39]	[0.71]	[1.12]	[-0.60]	[0.93]	[0.93]	[0.90]	[-2.01]
FF4 alpha	−0.22	0.17	0.27	−0.09	0.22	0.28*	−0.01	0.20	0.21	0.18	−0.39
	[-1.22]	[0.98]	[1.46]	[-0.52]	[1.47]	[1.92]	[-0.08]	[1.34]	[1.19]	[0.81]	[-1.19]

Table IA.2: Betting against beta- and (idiosyncratic) volatility in coskew-portfolios

This Table reports equity excess returns of betting against beta and volatility. In Panel A, we compute the returns of buying low and selling high CAPM beta stocks (betting against beta). Similarly we compute the returns to buying low risk and selling high risk stocks using idiosyncratic volatility relative to the CAPM (Panel B), idiosyncratic volatility relative to the Fama French three factor model (Panel C), and ex-ante variance (Panel D) as risk measures. In each panel, the first two columns report excess returns of betting against risk using quintile and decile portfolios, respectively. The remaining columns report results from unconditional portfolio double-sorts. We sort firms into equally-weighted quintile portfolios based on their coskewness (measured as in Harvey and Siddique, 2000), where Coskew-P_1 and Cokew-P_5 contain firms with highest and lowest coskewness, respectively. Independent of the coskew-sorts, we also sort firms into equally-weighted quintile portfolios based on either their CAPM beta, idiosyncratic volatility, or their ex-ante variance. For every coskew portfolio, we compute the returns of betting against risk. The last column reports the $P_5 - P_1$ differential. We report raw excess returns and alphas of CAPM-, Fama-French three-, and four-factor regressions. Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by Andrews (1991). The sample period is January 1996 to August 2014.

Panel A. Betting against CAPM Beta

	Betting against Risk		Betting against Risk in Coskew Portfolios					
	5 Port.	10 Port	Coskew-P_1	Coskew-P_2	Coskew-P_3	Coskew-P_4	Coskew-P_5	$P_5 - P_1$
Excess return	0.07	−0.08	0.53	0.11	−0.06	−0.14	0.08	−0.45
	[0.11]	[-0.10]	[0.91]	[0.19]	[-0.10]	[-0.21]	[0.12]	[-1.43]
Std deviation	8.76	10.59	8.90	8.60	9.13	8.93	9.49	5.23
Skewness	−0.44	−0.50	−0.34	−0.45	−0.58	−0.33	−0.49	−0.25
Sharpe ratio	0.03	−0.02	0.21	0.04	−0.02	−0.05	0.03	−0.30
CAPM alpha	0.87**	0.92*	1.33***	0.87**	0.77*	0.66	0.88*	−0.44
	[2.04]	[1.87]	[3.24]	[1.98]	[1.77]	[1.41]	[1.66]	[-1.41]
FF3 alpha	0.76***	0.79**	1.23***	0.81**	0.64**	0.53	0.78**	−0.45
	[2.61]	[2.23]	[3.76]	[2.44]	[2.21]	[1.37]	[2.01]	[-1.50]
FF4 alpha	0.42	0.39	0.86**	0.48	0.27	0.24	0.49	−0.37
	[1.14]	[0.87]	[2.37]	[1.20]	[0.74]	[0.52]	[1.10]	[-1.18]

(continued on next page)

Table IA.2 *(continued)*

Panel B. Betting against CAPM idiosyncratic volatility

	Betting against Risk		Betting against Risk in Coskew Portfolios					
	5 Port.	10 Port	Coskew-P_1	Coskew-P_2	Coskew-P_3	Coskew-P_4	Coskew-P_5	$P_5 - P_1$
Excess return	0.15	0.32	0.49	0.08	0.01	0.14	0.12	−0.37
	[0.25]	[0.46]	[0.83]	[0.14]	[0.01]	[0.24]	[0.18]	[-1.33]
Std deviation	9.19	10.80	9.68	9.19	9.25	9.03	9.51	4.54
Skewness	−0.63	−0.69	−0.74	−0.64	−0.82	−0.64	−0.54	−0.30
Sharpe ratio	0.06	0.10	0.17	0.03	0.00	0.05	0.04	−0.28
CAPM alpha	0.88**	1.22**	1.22***	0.76*	0.72	0.86*	0.84	−0.38
	[1.99]	[2.47]	[2.86]	[1.79]	[1.62]	[1.91]	[1.57]	[-1.26]
FF3 alpha	0.81***	1.17***	1.19***	0.72**	0.67**	0.79***	0.76**	−0.43
	[3.40]	[4.31]	[4.31]	[2.57]	[2.43]	[2.64]	[2.57]	[-1.48]
FF4 alpha	0.49	0.79**	0.83***	0.38	0.37	0.48	0.49	−0.34
	[1.67]	[2.33]	[2.65]	[1.42]	[1.17]	[1.48]	[1.49]	[-1.21]

Panel C. Betting against FF3 idiosyncratic volatility

	Betting against Risk		Betting against Risk in Coskew Portfolios					
	5 Port.	10 Port	Coskew-P_1	Coskew-P_2	Coskew-P_3	Coskew-P_4	Coskew-P_5	$P_5 - P_1$
Excess return	0.18	0.29	0.49	0.14	−0.01	0.20	0.21	−0.27
	[0.35]	[0.49]	[0.96]	[0.30]	[-0.01]	[0.38]	[0.35]	[-1.15]
Std deviation	7.98	9.10	8.14	8.08	8.00	7.93	8.55	4.53
Skewness	−0.77	−0.82	−0.73	−1.05	−0.98	−0.71	−0.63	−0.26
Sharpe ratio	0.08	0.11	0.21	0.06	−0.00	0.09	0.09	−0.21
CAPM alpha	0.81**	1.02**	1.09***	0.74*	0.59	0.83**	0.85*	−0.24
	[2.06]	[2.27]	[2.81]	[1.95]	[1.55]	[2.06]	[1.73]	[-0.85]
FF3 alpha	0.75***	0.98***	1.07***	0.77***	0.56**	0.77***	0.74**	−0.33
	[3.58]	[3.72]	[4.25]	[3.30]	[2.54]	[2.79]	[2.58]	[-1.20]
FF4 alpha	0.43*	0.57**	0.72***	0.42*	0.22	0.47	0.46	−0.26
	[1.80]	[2.26]	[3.10]	[1.85]	[0.94]	[1.58]	[1.56]	[-0.96]

Panel D. Betting against ex-ante variance

	Betting against Risk		Betting against Risk in Coskew Portfolios					
	5 Port.	10 Port	Coskew-P_1	Coskew-P_2	Coskew-P_3	Coskew-P_4	Coskew-P_5	$P_5 - P_1$
Excess return	0.02	0.06	0.48	−0.08	−0.16	0.10	−0.15	−0.62**
	[0.03]	[0.08]	[0.86]	[-0.14]	[-0.25]	[0.17]	[-0.23]	[-2.02]
Std deviation	9.40	11.22	9.32	9.48	9.32	9.52	9.97	4.39
Skewness	−0.86	−0.93	−0.58	−0.93	−1.06	−0.76	−0.93	−0.53
Sharpe ratio	0.01	0.02	0.18	−0.03	−0.06	0.04	−0.05	−0.49
CAPM alpha	0.78*	0.97*	1.21***	0.64	0.57	0.87*	0.63	−0.59**
	[1.73]	[1.79]	[2.89]	[1.39]	[1.17]	[1.86]	[1.14]	[-1.95]
FF3 alpha	0.73***	0.91***	1.16***	0.63**	0.55*	0.80**	0.58*	−0.58**
	[2.77]	[2.81]	[4.02]	[2.00]	[1.71]	[2.51]	[1.77]	[-2.03]
FF4 alpha	0.33	0.39	0.74**	0.20	0.18	0.42	0.19	−0.55*
	[1.05]	[1.09]	[2.29]	[0.63]	[0.50]	[1.18]	[0.56]	[-1.91]

Table IA.3: Portfolios sorted by lagged ex-ante skewness

This Table summarizes firm characteristics and equity returns across skew-portfolios. At the end of every month, we rank firms based on their ex-ante skewness measured on the business day before the portfolio formation and assign firms to portfolios, with P_1 (P_{10}) containing firms with highest (lowest) skewness. Panel A presents portfolio sample averages for firms' risk characteristics. We report ex-ante skewness (annualized, in percent), three measures of coskewness ($Cov_0^{\mathbb{P}}(R^2, R_i)$ denoting the covariation of firm equity excess returns and squared market excess returns as well as the coskewness measures of Kraus and Litzenberger (1976) and Harvey and Siddique (2000)), conditional CAPM betas, idiosyncratic volatility estimated from the residual variance of CAPM and Fama French three-factor regressions (both estimates are monthly, in percent), and ex-ante variance (annualized, in percent). Size refers to firms' market capitalization (in billion US dollars) and B/M denotes book-to-market ratios. In Panels B and C, we present the returns of equally-weighted portfolios and value-weighted portfolios, respectively. We report monthly equity returns (in percentage points) for individual portfolios as well as the $P_1 - P_{10}$ differential (HL). We report raw excess returns along with standard deviations and Sharpe ratios (annualized), as well as alphas of CAPM-, Fama-French three-, and four-factor regressions. Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by Andrews (1991). The data covers 4,967 US firms, is sampled at a monthly frequency over the period January 1996 to August 2014, and contains a total of 400,449 observations.

Panel A. Equity returns of portfolios sorted by lagged ex-ante skewness: Equally-weighted

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	HL
Excess return	1.63***	1.32**	1.24**	1.03**	0.84*	0.76*	0.67	0.49	0.30	0.03	1.59***
	[2.93]	[2.47]	[2.38]	[2.02]	[1.86]	[1.67]	[1.56]	[1.14]	[0.73]	[0.09]	[4.43]
Std deviation	7.57	7.62	7.26	6.77	6.36	6.17	5.97	5.75	5.49	5.01	4.46
Skewness	0.15	0.05	−0.16	−0.35	−0.38	−0.42	−0.48	−0.84	−0.82	−1.07	1.37
Sharpe ratio	0.74	0.60	0.59	0.53	0.46	0.43	0.39	0.30	0.19	0.02	1.24
CAPM alpha	0.80***	0.47*	0.41*	0.24	0.10	0.04	−0.03	−0.19	−0.34**	−0.53***	1.33***
	[2.66]	[1.90]	[1.71]	[1.10]	[0.54]	[0.20]	[-0.16]	[-1.09]	[-2.42]	[-2.90]	[4.37]
FF3 alpha	0.61***	0.34	0.26	0.08	−0.05	−0.13	−0.18	−0.35***	−0.52***	−0.71***	1.33***
	[2.68]	[1.56]	[1.52]	[0.53]	[-0.40]	[-1.13]	[-1.49]	[-3.31]	[-4.44]	[-5.40]	[4.61]
FF4 alpha	0.87***	0.57***	0.44***	0.23*	0.07	−0.04	−0.07	−0.30***	−0.46***	−0.68***	1.55***
	[3.58]	[2.83]	[3.00]	[1.77]	[0.62]	[-0.39]	[-0.69]	[-2.65]	[-4.24]	[-5.29]	[5.01]

Panel B. Equity returns of portfolios sorted by lagged ex-ante skewness: Value-weighted

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	HL
Excess return	0.89**	0.98**	1.06**	0.89**	0.84**	0.69*	0.83**	0.66*	0.23	−0.01	0.90***
	[1.97]	[2.09]	[2.24]	[2.25]	[2.28]	[1.85]	[2.45]	[1.86]	[0.61]	[-0.04]	[2.84]
Std deviation	6.45	6.91	6.42	5.94	5.99	5.42	5.05	4.98	5.25	4.41	4.68
Skewness	0.00	−0.15	−0.08	−0.37	−0.60	−0.28	−0.03	−0.65	−0.73	−0.81	0.53
Sharpe ratio	0.48	0.49	0.57	0.52	0.49	0.44	0.57	0.46	0.15	−0.01	0.67
CAPM alpha	0.22	0.23	0.35*	0.22	0.18	0.05	0.26	0.08	−0.38***	−0.50***	0.72**
	[1.08]	[1.13]	[1.75]	[1.40]	[1.00]	[0.36]	[1.37]	[0.58]	[-3.10]	[-3.27]	[2.50]
FF3 alpha	0.16	0.19	0.37*	0.22	0.21	0.05	0.22	0.03	−0.42***	−0.57***	0.73***
	[0.86]	[0.90]	[1.86]	[1.37]	[1.26]	[0.38]	[1.19]	[0.25]	[-3.45]	[-3.75]	[2.74]
FF4 alpha	0.47***	0.49**	0.55***	0.40**	0.39**	0.13	0.37**	0.12	−0.36***	−0.52***	1.00***
	[2.78]	[2.37]	[2.60]	[2.22]	[2.42]	[1.09]	[2.15]	[1.32]	[-2.80]	[-3.49]	[3.71]

Table IA.4: Betting against beta- and (idiosyncratic) volatility in lagged skew-portfolios

This Table reports equity excess returns of betting against beta and volatility. In Panel A, we compute the returns of buying low and selling high CAPM beta stocks (betting against beta). Similarly we compute the returns to buying low risk and selling high risk stocks using idiosyncratic volatility relative to the CAPM (Panel B), idiosyncratic volatility relative to the Fama French three factor model (Panel C), and ex-ante variance (Panel D) as risk measures. In each panel, the first two columns report excess returns of betting against risk using quintile and decile portfolios, respectively. The remaining columns report results from unconditional portfolio double-sorts. We sort firms into equally-weighted quintile portfolios based on their ex-ante skewness measured on the business day before the portfolio formation, where Skew-P_1 and Skew-P_5 contain firms with highest and lowest ex-ante skewness, respectively. Independent of the skew-sorts, we also sort firms into equally-weighted quintile portfolios based on either their CAPM beta, idiosyncratic volatility, or their ex-ante variance. For every skew portfolio, we compute the returns of betting against risk. The last column reports the $P_5 - P_1$ differential. We report raw excess returns and alphas of CAPM-, Fama-French three-, and four-factor regressions. Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by Andrews (1991). The sample period is January 1996 to August 2014.

Panel A. Betting against CAPM Beta

	Betting against Risk		Betting against Risk in Skew Portfolios					
	5 Port.	10 Port	Skew-P_1	Skew-P_2	Skew-P_3	Skew-P_4	Skew-P_5	$P_5 - P_1$
Excess return	0.08	−0.07	−0.14	−0.22	0.35	0.44	0.94*	1.08***
	[0.13]	[-0.10]	[-0.20]	[-0.33]	[0.64]	[0.74]	[1.71]	[3.27]
Std deviation	8.77	10.58	9.96	9.63	8.40	8.19	7.86	5.31
Skewness	−0.43	−0.50	−0.61	−0.65	−0.20	−0.14	0.00	0.96
Sharpe ratio	0.03	−0.02	−0.05	−0.08	0.15	0.19	0.42	0.71
CAPM alpha	0.88**	0.92*	0.72	0.62	1.10***	1.18***	1.64***	0.92***
	[2.05]	[1.87]	[1.35]	[1.27]	[2.66]	[2.82]	[4.11]	[2.95]
FF3 alpha	0.76***	0.79**	0.57	0.49	0.94***	1.03***	1.59***	1.02***
	[2.62]	[2.22]	[1.35]	[1.36]	[3.55]	[3.31]	[4.62]	[2.94]
FF4 alpha	0.42	0.38	0.19	0.15	0.65**	0.76**	1.33***	1.14***
	[1.13]	[0.85]	[0.37]	[0.37]	[2.00]	[2.13]	[3.46]	[3.21]

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Table IA.4 *(continued)*

Panel B. Betting against CAPM idiosyncratic volatility

	Betting against Risk		Betting against Risk in Skew Portfolios					
	5 Port.	10 Port	Skew-P_1	Skew-P_2	Skew-P_3	Skew-P_4	Skew-P_5	$P_5 - P_1$
Excess return	0.16	0.31	−0.13	−0.05	0.75	0.89	0.96	1.09***
	[0.26]	[0.45]	[-0.20]	[-0.08]	[1.28]	[1.45]	[1.54]	[3.20]
Std deviation	9.20	10.82	10.12	9.69	8.80	8.78	8.42	4.89
Skewness	−0.63	−0.69	−0.68	−0.68	−0.24	−0.42	−0.42	0.51
Sharpe ratio	0.06	0.10	−0.04	−0.02	0.29	0.35	0.39	0.77
CAPM alpha	0.89**	1.21**	0.67	0.70	1.40***	1.60***	1.56***	0.88***
	[2.00]	[2.44]	[1.43]	[1.53]	[3.07]	[3.43]	[3.15]	[2.88]
FF3 alpha	0.81***	1.15***	0.55*	0.64**	1.31***	1.52***	1.55***	1.00***
	[3.43]	[4.32]	[1.65]	[2.45]	[5.77]	[6.00]	[4.44]	[3.13]
FF4 alpha	0.50*	0.77**	0.23	0.31	1.05***	1.27***	1.32***	1.10***
	[1.67]	[2.28]	[0.63]	[0.87]	[4.70]	[4.34]	[3.69]	[3.44]

Panel C. Betting against FF3 idiosyncratic volatility

	Betting against Risk		Betting against Risk in Skew Portfolios					
	5 Port.	10 Port	Skew-P_1	Skew-P_2	Skew-P_3	Skew-P_4	Skew-P_5	$P_5 - P_1$
Excess return	0.18	0.29	−0.04	0.10	0.50	0.57	1.05**	1.09***
	[0.35]	[0.51]	[-0.07]	[0.18]	[1.02]	[1.17]	[2.01]	[3.81]
Std deviation	7.99	9.11	8.78	8.23	7.98	7.64	7.17	4.60
Skewness	−0.76	−0.81	−0.65	−0.77	−0.69	−0.53	−0.61	0.11
Sharpe ratio	0.08	0.11	−0.02	0.04	0.22	0.26	0.51	0.82
CAPM alpha	0.81**	1.03**	0.67	0.70	1.04**	1.16***	1.57***	0.89***
	[2.04]	[2.28]	[1.60]	[1.64]	[2.46]	[2.79]	[3.91]	[3.14]
FF3 alpha	0.75***	0.99***	0.58*	0.64***	0.95***	1.12***	1.56***	0.98***
	[3.56]	[3.77]	[1.89]	[2.78]	[4.50]	[4.87]	[5.63]	[3.40]
FF4 alpha	0.42*	0.57**	0.23	0.29	0.68***	0.86***	1.32***	1.09***
	[1.75]	[2.28]	[0.67]	[1.09]	[2.61]	[3.41]	[4.83]	[3.85]

Panel D. Betting against ex-ante variance

	Betting against Risk		Betting against Risk in Skew Portfolios					
	5 Port.	10 Port	Skew-P_1	Skew-P_2	Skew-P_3	Skew-P_4	Skew-P_5	$P_5 - P_1$
Excess return	0.02	0.06	−0.25	−0.15	0.71	0.72	1.14*	1.39***
	[0.03]	[0.09]	[-0.40]	[-0.23]	[1.11]	[1.15]	[1.90]	[4.51]
Std deviation	9.42	11.26	10.00	10.09	9.49	9.18	8.76	4.83
Skewness	−0.85	−0.92	−0.88	−0.96	−0.62	−0.47	−0.60	0.57
Sharpe ratio	0.01	0.02	−0.09	−0.05	0.26	0.27	0.45	1.00
CAPM alpha	0.78*	0.97*	0.57	0.65	1.42***	1.49***	1.78***	1.21***
	[1.73]	[1.78]	[1.26]	[1.32]	[2.71]	[3.25]	[3.60]	[4.09]
FF3 alpha	0.73***	0.91***	0.49	0.60**	1.37***	1.46***	1.75***	1.26***
	[2.75]	[2.82]	[1.52]	[2.00]	[4.75]	[4.76]	[4.88]	[4.28]
FF4 alpha	0.33	0.39	0.12	0.15	1.03***	1.04***	1.41***	1.29***
	[1.01]	[1.09]	[0.34]	[0.48]	[3.33]	[3.43]	[3.82]	[4.47]

Table IA.5: Robustness to number of portfolios and return weighting schemes

This Table reports results for unconditional portfolio double-sorts. At the end of every month, we sort firms into N portfolios based on their ex-ante skewness and, independently, in N portfolios based on their CAPM beta (Panel A), idiosyncratic volatility relative to the CAPM (Panel B) and relative to the Fama French factors (Panel C), and based on their ex-ante variance (Panel D). In each skew portfolio we compute the returns of betting against beta/volatility and from these we compute the differential returns of betting against beta/volatility in the low skew portfolio minus betting against beta/volatility in the high skew portfolio (analogue to Table 2). We present results for $N \in (5, 7, 10)$ using equally-weighted portfolios (first three columns), value-weighted portfolios (middle three columns), and rank weighted portfolios (last three columns). We report raw excess returns as well as alphas of CAPM-, Fama-French three-, and four-factor regressions. Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by Andrews (1991). The sample period is January 1996 to August 2014.

Panel A. Betting against CAPM Beta

	Equally-weighted			Value-weighted			Rank-weighted		
	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port
Excess return	1.04***	1.91***	2.04***	0.15	1.00**	1.86**	1.26***	2.10***	2.52***
	[2.73]	[4.04]	[2.88]	[0.24]	[2.09]	[2.00]	[2.86]	[3.70]	[2.98]
CAPM alpha	0.87**	1.74***	1.81**	−0.17	0.75	1.46*	1.10**	1.89***	2.10***
	[2.32]	[3.46]	[2.53]	[-0.30]	[1.31]	[1.72]	[2.43]	[3.43]	[2.68]
FF3 alpha	0.84**	1.75***	1.86***	−0.23	0.74	1.53*	1.03**	1.93***	2.19**
	[2.02]	[3.20]	[2.71]	[-0.46]	[1.38]	[1.79]	[2.07]	[3.36]	[2.46]
FF4 alpha	1.15**	2.00***	1.96**	0.15	1.09**	1.89**	1.32**	2.16***	2.57***
	[2.50]	[3.24]	[2.45]	[0.28]	[1.99]	[2.41]	[2.48]	[3.33]	[2.84]

(continued on next page)

Table IA.5 *(continued)*

Panel B. Betting against CAPM idiosyncratic volatility

	Equally-weighted			Value-weighted			Rank-weighted		
	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port
Excess return	1.65***	1.72***	2.77***	0.91	1.70**	2.67***	1.75***	2.01***	2.85***
	[4.55]	[3.76]	[3.58]	[1.37]	[2.36]	[2.99]	[4.32]	[3.77]	[3.06]
CAPM alpha	1.38***	1.42***	2.44***	0.45	1.22*	2.26***	1.44***	1.69***	2.50***
	[4.22]	[3.27]	[3.17]	[0.69]	[1.77]	[2.69]	[4.23]	[3.48]	[2.85]
FF3 alpha	1.41***	1.54***	2.58***	0.51	1.48**	2.64***	1.49***	1.82***	2.66***
	[4.13]	[3.81]	[3.30]	[0.81]	[2.55]	[3.39]	[4.22]	[4.17]	[2.95]
FF4 alpha	1.58***	1.71***	2.81***	0.75	1.81***	2.73***	1.68***	2.00***	2.97***
	[5.12]	[4.35]	[3.37]	[1.04]	[2.61]	[2.77]	[5.46]	[4.02]	[3.07]

Panel C. Betting against FF3 idiosyncratic volatility

	Equally-weighted			Value-weighted			Rank-weighted		
	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port
Excess return	1.20***	1.70***	1.79***	0.89**	1.25	0.93	1.24***	1.66***	1.62**
	[3.25]	[3.43]	[2.81]	[2.43]	[1.32]	[1.11]	[2.87]	[2.94]	[2.32]
CAPM alpha	0.91***	1.41***	1.57**	0.38	0.76	0.55	0.96**	1.35***	1.28**
	[2.78]	[3.19]	[2.53]	[0.80]	[0.87]	[0.69]	[2.42]	[2.75]	[2.08]
FF3 alpha	1.04***	1.52***	1.63**	0.62	1.04	0.74	1.06***	1.42***	1.32**
	[3.41]	[3.21]	[2.45]	[1.38]	[1.36]	[1.02]	[2.80]	[2.67]	[2.00]
FF4 alpha	1.21***	1.67***	1.80**	1.05*	1.43	1.12	1.26***	1.62***	1.65**
	[3.90]	[3.41]	[2.57]	[1.74]	[1.35]	[1.25]	[3.29]	[2.96]	[2.49]

Panel D. Betting against ex-ante variance

	Equally-weighted			Value-weighted			Rank-weighted		
	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port
Excess return	1.85***	2.75***	2.60***	1.79***	2.90***	1.84*	2.25***	2.98***	2.43***
	[5.80]	[5.49]	[3.84]	[3.06]	[3.55]	[1.91]	[5.22]	[5.38]	[2.89]
CAPM alpha	1.55***	2.37***	2.20***	1.31*	2.47***	1.48*	1.93***	2.59***	2.01**
	[4.98]	[4.69]	[3.43]	[1.71]	[3.18]	[1.68]	[4.86]	[5.01]	[2.47]
FF3 alpha	1.65***	2.59***	2.43***	1.42*	2.71***	1.86*	2.09***	2.83***	2.29***
	[4.72]	[5.22]	[3.52]	[1.76]	[3.46]	[1.90]	[4.97]	[5.35]	[2.73]
FF4 alpha	1.76***	2.71***	2.74***	1.74**	3.03***	2.27*	2.21***	3.06***	2.62***
	[4.95]	[5.34]	[3.44]	[2.09]	[3.37]	[1.91]	[5.38]	[5.28]	[2.73]

Table IA.6: Robustness to conditional portfolio double sorts

This Table reports results for conditional portfolio double-sorts. The first three columns report results of betting against beta/volatility in skew-sorted portfolios, i.e. we first sort firms into N portfolios based on their ex-ante skewness, and, subsequently, within each skew portfolio, we sort firms into N portfolios based on beta/volatility. We then compute the differential returns of betting against beta/volatility in the low skew portfolio minus betting against beta/volatility in the high skew portfolio (analogue to Table 2). The last three columns report results of betting on skewness ibeta/volatility-sorted portfolios, i.e. we first sort firms into N portfolios based on their beta/volatility and, subsequently, within each beta/volatility portfolio, we sort firms into N portfolios based on ex-ante skewness. We then compute the differential returns of betting on skewness in the high beta/volatility portfolio minus betting on skewness in the low beta/ volatility portfolio (analogue to Table 3). We present results for equally-weighted portfolios, using $N \in (5, 7, 10)$, based on firms' CAPM beta (Panel A), idiosyncratic volatility relative to the CAPM (Panel B) and relative to the Fama French factors (Panel C), and based on their ex-ante variance (Panel D). We report raw excess returns as well as alphas of CAPM-, Fama-French three-, and four-factor regressions. Values in square brackets are t-statistics based on standard errors following Newey and West (1987) where we choose the optimal truncation lag as suggested by Andrews (1991). The sample period is January 1996 to August 2014.

Panel A. Betting against CAPM Beta

	Betting against Beta/Vola			Betting on Skewness		
	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port
Excess return	0.59	1.00*	1.48**	0.73*	0.74	1.11*
	[1.28]	[1.73]	[2.09]	[1.88]	[1.54]	[1.87]
CAPM alpha	0.30	0.64	1.12	0.61*	0.60	0.98*
	[0.66]	[1.13]	[1.57]	[1.64]	[1.25]	[1.66]
FF3 alpha	0.38	0.71	1.23	0.57	0.57	0.97
	[0.80]	[1.19]	[1.62]	[1.54]	[1.08]	[1.47]
FF4 alpha	0.69	1.07	1.59**	0.86**	0.88	1.32*
	[1.28]	[1.64]	[2.07]	[2.18]	[1.55]	[1.72]

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Table IA.6 *(continued)*

Panel B. Betting against CAPM idiosyncratic volatility

	Betting against Beta/Vola			Betting on Skewness		
	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port
Excess return	0.88**	1.13**	1.57**	1.05***	1.42***	1.58***
	[2.04]	[2.15]	[2.34]	[3.02]	[3.50]	[3.02]
CAPM alpha	0.48	0.71	1.13*	0.90**	1.20***	1.35***
	[1.29]	[1.62]	[1.95]	[2.61]	[3.16]	[2.70]
FF3 alpha	0.65*	0.85*	1.29**	0.90**	1.17***	1.29***
	[1.71]	[1.90]	[2.21]	[2.55]	[3.01]	[2.57]
FF4 alpha	0.92**	1.10**	1.55**	1.08***	1.41***	1.47***
	[2.33]	[2.39]	[2.53]	[3.11]	[3.59]	[3.11]

Panel C. Betting against FF3 idiosyncratic volatility

	Betting against Beta/Vola			Betting on Skewness		
	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port
Excess return	0.71*	1.16**	1.25*	0.82**	1.12**	1.69***
	[1.83]	[2.27]	[1.86]	[2.10]	[2.55]	[3.14]
CAPM alpha	0.43	0.84*	0.87	0.64*	0.96**	1.63***
	[1.23]	[1.90]	[1.47]	[1.70]	[2.28]	[3.09]
FF3 alpha	0.52	0.97**	0.93	0.67*	1.02**	1.59***
	[1.58]	[2.28]	[1.62]	[1.74]	[2.22]	[2.90]
FF4 alpha	0.79**	1.19***	1.19**	0.83**	1.16**	1.67***
	[2.32]	[2.57]	[2.42]	[2.08]	[2.39]	[2.84]

Panel D. Betting against ex-ante variance

	Betting against Beta/Vola			Betting on Skewness		
	5 Port	7 Port	10 Port	5 Port	7 Port	10 Port
Excess return	0.91**	1.33**	2.42***	1.55***	2.10***	2.30***
	[2.03]	[2.53]	[3.30]	[5.25]	[5.23]	[4.46]
CAPM alpha	0.59	0.96**	1.98***	1.47***	1.99***	2.21***
	[1.37]	[1.99]	[3.01]	[5.06]	[4.72]	[4.27]
FF3 alpha	0.84**	1.25***	2.19***	1.51***	2.04***	2.18***
	[2.23]	[2.97]	[3.39]	[5.00]	[4.72]	[4.56]
FF4 alpha	1.08***	1.46***	2.37***	1.68***	2.22***	2.32***
	[2.65]	[3.34]	[3.76]	[5.25]	[5.09]	[4.53]