Low Risk Anomalies?

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Summary of main results and relevance to Q-Group

Based on the intriguing empirical evidence that high-volatility and high-beta stocks underperform low-volatility and low-beta stocks, many investment managers follow strategies designed to exploit these - apparently anomalous - patterns. Our paper shows that the profitability of betting-against-beta and betting against-volatility strategies does not pose an asset pricing puzzle when accounting for the skewness of firms' stock returns. Consistent with our theoretical model, we find that the performance of such trading strategies is closely related to firms' downside risk. The intuition is that failure to account for skewness leads to a biased estimation of a firm's market risk. More specifically, the higher a firm's downside risk, the more the beta in the standard capital asset pricing model (CAPM) overestimates the firm's true market risk. Hence the returns of such stocks appear anomalously low when benchmarked against the (overestimated) CAPM beta whereas they just reflect adequate compensation for true (skew-adjusted) market risk.

Our empirical results, based on a sample of almost 5,000 US firms from 1996 to 2014, provide the following main implications for investment managers:

Selection of stocks: Since the profitability of betting-against-beta/volatility strategies does depend on firms' skewness, such trading strategies could be extended to take skewness into account. We show that the excess return differential of betting-against-beta/volatility strategies for positively compared to negatively skewed stocks is more than 1% per month after controlling for standard risk factors.

Skewness as a driver of performance: our results suggest that (i) betting-against-beta/volatility strategies collect premia that compensate for skewness and (ii) that the downside risk of such strategies should be closely monitored and managed.

Equity returns and distress risk: our results also offer a novel perspective on the distress puzzle, defined as the empirical finding that distressed firms earn anomalously low stock returns. Given that credit risk is a driver of firms' skewness this credit-linked low risk anomaly is related to beta/volatility-anomalies, implying that (i) the performance of trading on distress risk and betting-against-beta/volatility are related, (ii) distress strategies can be extended by skewness-signals, (iii) betting-against-beta/volatility strategies can be extended by credit signals.

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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 that endogenizes the role of skewness for stock returns through default risk. With increasing downside risk, the standard capital asset pricing model (CAPM) increasingly overestimates expected equity returns relative to firms' true (skew-adjusted) market risk. Empirically, the profitability of betting against beta/volatility increases with firms' downside risk, and the risk-adjusted return differential of betting against beta/volatility among low skew firms compared to high skew firms is economically large. Our results suggest that the returns to betting against beta or volatility do not necessarily pose asset pricing puzzles but rather that such strategies collect premia that compensate for skew risk. Since skewness is directly connected to default risk, our results also provide insights for the distress puzzle.

Keywords: Low risk anomaly, risk premia, credit risk, skewness, equity options, cross-sectional asset pricing.

1 Introduction

Empirical patterns such as the 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; Frazzini and Pedersen, 2014). This paper shows that the returns to trading such anomalies can be rationalized when accounting for the skewness of equity returns, which standard measures of market risk and (idiosyncratic) volatility ignore.

To motivate our claim, we employ an asset pricing model that uses the market as systematic risk factor, that nests the standard Capital Asset Pricing Model (CAPM), but that also accounts for higher moments of the return distribution. To assess the relevance of higher order moments in asset pricing, we embed the credit risk model of Merton (1974) in our market model. Default risk acts as a natural source of skewness in returns that affects the joint distribution of firm equity and market returns. With increasing credit risk, the CAPM beta increasingly overestimates a 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 just reflect the firm's true market risk. Given that the CAPM systematically overestimates expected equity returns, idiosyncratic volatility measured from CAPM pricing errors should convey return-relevant information as well.

Our empirical results strongly support the predictions derived from the model. We show that ex-ante skew predicts the cross-section of equity returns and that conditioning on ex-ante skew 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 overestimation 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 the 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 the more negative, the more expensive put options are relative to call options, i.e. if investors are willing to pay high premia for 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 equity returns: high skew firms 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. These equity returns are associated with an identical pattern for realized skewness, with realized skewness monotonically declining from the high to the low ex-ante skewness portfolio.

Having established that ex-ante skew 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. Fama-French-Carhart four factor model alphas range from 1.15% and 1.76% per month and the performance is not driven by specific sample periods but delivers steady returns over time.

Moreover, we show that our results also provide a new perspective on the distress puzzle, a credit risk-related low risk anomaly, defined as the lack of a positive relation between distress risk and equity returns (e.g., Campbell et al., 2008). The direct link between skewness and credit risk allows to recast the results for skew-sorted portfolios from a credit risk angle. The firms with highest credit risk (i.e. most negative ex-ante skewness) earn the lowest stock returns, a pattern that matches the distress puzzle. At the same time, we show that these firms generate highest skew risk premia, measured as realized skewness minus ex-ante skewness. These results are consistent with recent research finding an inverse relation between equity returns and credit risk premia (e.g., Friewald et al., 2014) and supports the notion that option prices reflect skew preferences (e.g., Bali and Murray, 2012). More generally, these results illustrates that default risk creates higher-moment risk that affects the entire shape of the return distribution and not only expected returns. It also suggests that compensation for corporate credit risk and compensation for crash risk in the aggregate market seem to follow similar channels, as the latter has recently also been shown to be related to higher order preferences and (index) option-implied risk premia.

Various robustness checks confirm our empirical findings and corroborate our conclusions. Essentially, our theoretical and empirical results suggest that empirical patterns labeled as low risk anomalies may not necessarily pose asset pricing puzzles when accounting for higher moments of the return distribution. While our setup relates to earlier work that emphasizes the relevance of higher moment preferences (e.g., Kraus and Litzenberger, 1976; Harvey and Siddique, 2000), a key feature of our asset pricing framework is that we embed a model of credit risk and thereby endogenize the role of skewness for equity returns. As a consequence, the CAPM beta may not be a sufficient metric to judge a firm's market risk, and 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 and credit risk to equity returns.

Related Literature. While the CAPM 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 tests of the CAPM coming to this conclusion include 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. Campbell et al. (2014) rationalize the latter finding by extending the intertemporal CAPM (Campbell, 1993) to allow for stochastic volatility. Frazzini and Pedersen (2014) present a model where leverage constrained investors bid up high-beta assets which in turn generate low risk-adjusted returns. Baker et al. (2011) argue that institutional investors' mandate to beat a fixed benchmark discourages arbitrage activity and thereby contributes to the anomaly. Bali et al. (2014) find that the anomaly is consistent with investors' preference for holding stocks with lottery-like payoffs. 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.

This paper takes a different approach by directly linking low risk anomalies to return skewness. 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 co-skewness with the market entails information for stock returns beyond co-variance, 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. 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. Xing et al., 2010; Rehman and Vilkov, 2012; Conrad et al., 2013), with differences in results driven by differences in skew-measure construction. 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. Hence, differences in their results are likely to reflect the finding of An et al. (2014) that changes implied volatilities (IVs) of call options and put options have a differential impact on stock returns. Moreover, their explanation based on informed traders preferring to trade in the options market first, allows to connect the positive relation between ex-ante skew and stock returns to the evidence of Bali and Murray (2012) that ex-ante skew predicts the cross-section of option returns consistent with skew preferences. Related, Bali et al. (2015) show 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 model implies, and the empirical results confirm, that betting against beta or volatility is profitable for firms with high downside risk, but generates losses among firms with less negative or positive ex-ante skewness. Thus, we provide novel insights on the prevalence of low risk anomalies by establishing a direct link to skew-related CAPM mispricing. While the model's endogenous source of skewness is credit risk, we discuss that the asset pricing implications also apply when skewness is driven by other sources. As such, our results can also be connected to previous explanations to the extent that skewness plays a role (at least indirectly). For instance, our results are consistent with findings that accounting for the lottery characteristics of stocks reverses the relation between idiosyncratic volatility and equity returns (Bali et al., 2011) and reduces the returns of betting against beta (Bali et al., 2014). Moreover, since skewness is directly linked to credit risk in our model as well as empirically (e.g., Hull et al., 2005; Carr and Wu, 2009, 2011), our work also provides new insights on the distress puzzle (e.g. Dichev, 1998; Vassalou and Xing, 2004; Campbell et al., 2008), and complements recent research that provides evidence for a link between credit risk premia and equity returns (e.g. Friewald et al., 2014).

The remainder of the 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 concludes.

2 Theoretical Framework

In this Section, we develop 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 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, 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. Our theoretical results suggest that accounting for (credit risk-induced) skewness adds insights for low risk anomalies and we explore the empirical validity of the model's implications in Section 4.

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 an arbitrage-free economy with a representative power utility investor. We assume that the market exhibits stochastic volatility (Heston, 1993) and model the dynamics of the forward market price $M_{t,T}$, contracted at time t for delivery at T, as [1]

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

With γ denoting the coefficient of constant relative risk aversion, $\eta_t = \gamma\kappa_t^2$ denotes the instantaneous market return in excess of the risk-free rate and κ_t is the associated market volatility. Campbell et al. (2014) develop an empirically successful asset pricing model

[1] 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.

with stochastic volatility in a similar way.[2] 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 $M_{0,T} = 1$. The power utility function of the representative agent is given by $U := ((R+1)^{1-\gamma} - 1)/(1-\gamma)$, where $\gamma > 0$. Given the agent's preferences, we obtain the forward pricing kernel ($\mathcal{M}$) as

$$\mathcal{M} := \frac{(R+1)^{-\gamma}}{\mathbb{E}_0^{\mathbb{P}}\left[(R+1)^{-\gamma}\right]} = \frac{(R+1)^{-\gamma}}{e^{1/2\int_0^T \kappa_s^2 ds(\gamma-\gamma^2)}}. \tag{2}$$

The pricing kernel is not measurable with respect to the market return R, but is also a function of integrated variance. For this reason 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 Equation (3) to first-order,[3]

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

where the coefficients a_1 and b_1 are functions of γ, T, and the parameters of the stochastic market variance process.[4] 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

[2]In Appendix A, we show that the less realistic but more parsimonious case of modeling the market by a geometric Brownian motion 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).

[3]The coefficients in the linear and quadratic forms (7) and (8) arise from a polynomial expansion of $\mathcal{M}$ in a L^2 space weighted with the $\mathbb{P}$ density of R.

[4]For space reasons we delegate exact expressions for the coefficients to Appendix A only in the simpler geometric Brownian motion case, but the structure of the coefficients is largely independent of a model.

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.[5]

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 (the only risk factor), scaled by asset i's covariation with the pricing kernel relative to the market's covariation with $\mathcal{M}(R)$,

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

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

[5] More generally, the economic notion of higher-order risk aversion (prudence, temperance) that in the expected utility framework is connected to alternating signs of derivatives of the marginal rate of substitution of the representative agent can be connected to preferences for signs and magnitudes of conditional moments (see Ebert, 2013).

return is given by the standard CAPM beta multiplied by the market risk premium,

$$\begin{aligned}\mathbb{E}_0^{\mathbb{P}}[R_i] &\approx \frac{Cov_0^{\mathbb{P}}(a_1+b_1R,R_i)}{Cov_0^{\mathbb{P}}(a_1+b_1R,R)}\,\mathbb{E}_0^{\mathbb{P}}[R] \\ &= \underbrace{\frac{Cov_0^{\mathbb{P}}(R,R_i)}{V_0^{\mathbb{P}}[R]}}_{\text{CAPM beta}}\,\mathbb{E}_0^{\mathbb{P}}[R]\,.\end{aligned} \tag{7}$$

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

$$\begin{aligned}\mathbb{E}_0^{\mathbb{P}}[R_i] &= \frac{Cov_0^{\mathbb{P}}(a_2+b_2R+c_2R^2,R_i)}{Cov_0^{\mathbb{P}}(a_2+b_2R+c_2R^2,R)}\mathbb{E}_0^{\mathbb{P}}[R] \\ &= \underbrace{\frac{b_2Cov_0^{\mathbb{P}}(R,R_i)+c_2Cov_0^{\mathbb{P}}(R^2,R_i)}{b_2V_0^{\mathbb{P}}[R]+c_2Cov_0^{\mathbb{P}}(R,R^2)}}_{\text{'skew-adjusted beta'}}\,\mathbb{E}_0^{\mathbb{P}}[R]\,.\end{aligned} \tag{8}$$

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 tackles the extent to which accounting for higher order risks such as skewness adds to

[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.

our understanding of low risk anomalies associated with the CAPM beta and measures of volatility.[7]

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

We now show that corporate credit risk generates time-varying skewness in a firm's equity returns, which in turn affects the pricing of its stock. To develop ideas, we use the model of Merton (1974) and show how credit risk matters for the shape of a firm's equity return distribution. We then incorporate credit risk into the market-based asset pricing framework (discussed in Section 2.1), by allowing asset value dynamics to contain systematic and idiosyncratic shocks. Within this Merton-market-world, we compute the firm's CAPM and its skew-adjusted beta to show that CAPM-betas increasingly overestimate a firm's true market risk as the firm's credit risk increases (equivalent to its ex-ante skewness becoming more negative). These results suggest that betting against beta should be most profitable for stocks with most negative return skewness but less so firms whose returns exhibit little skewness (low default risk).

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

[7] Put differently, we explore the extent to which the CAPM approximation error in asset pricing matters for understanding the cross-section of equity returns. Our results below confirm that approximation errors increase as higher-moment risk becomes more relevant, thereby shedding light on low risk anomalies. Note, however, that the approximation error will generally be non-zero in our setup since the pricing kernel is an exponential function of the log return and hence cannot be described without error with finite polynomials.

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 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).

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.Whereas Merton- and Black Scholes-implied distributions are virtually indistinguishable for firms with low credit risk (low leverage, Panels a and b), they are markedly different for firms with high credit risk (high leverage, Panels c and d). 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 the corresponding results 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.

In our empirical analysis, we measure ex-ante variance and skewness using data on equity options; in Section 3.2 we discuss in detail how out-of-the money equity options can be used to estimate $\mathbb{Q}$-measure variance and skewness. Therefore, we now show how credit risk affects option prices across strike prices in the Merton world. To make option prices comparable across moneyness levels, we consider implied volatilities (IVs). We measure the moneyness of an option on equity with strike K by $\log(K/F_{t,T})$, where $F_{t,T}$ is the forward on E_T. OTM puts therefore have negative moneyness and OTM calls have positive moneyness. We plot the IVs of OTM equity options across moneyness levels in Figure 3, for firms with high and low leverage in Panels (a) and (b), respectively. Equity options are more expensive for firms with high compared to low credit risk, where the difference in IV levels mainly reflects that equity volatility is higher for firms with high leverage. IVs generally decrease as moneyness increases, suggesting that put options are more expensive than call options, and that price differences become more extreme the further options are out-of-the-money. Taking a closer look at the IV scale on the y-axis reveals that the slope of the IV curve is very steep for high credit risk firms but almost flat for low credit risk firms. These results illustrate how the skew induced by credit risk affects prices of OTM put relative to OTM call options.

Panels (a) and (b) also contain plots of IVs evaluated under the $\mathbb{P}$-probability measure, i.e. 'pseudo prices' of options with expectations computed under the physical rather then the risk-neutral probability measure. Comparing IV to $\text{IV}^{\mathbb{P}}$ is interesting because it reveals information about risk premia embedded in option prices. The plots show that IV is always higher than $\text{IV}^{\mathbb{P}}$, implying that options prices contain a risk premium on top of the $\mathbb{P}$-expected option payoff. Panels (c) and (d) show that the risk premium monotonically decreases as moneyness increases, i.e. deep OTM put (call) options contain highest (lowest) risk premia. The IV-IV$^{\mathbb{P}}$ differences are very small for low leverage firms but sizeable for firms with credit risk. This pattern is consistent with the notion that risk premia required by sellers of protection against large decreases in the equity value increase with the firm's credit risk.

Having shown that credit risk acts as a natural source of skewness, our next step is to study the credit risk-related skew implications within the asset pricing framework described above in Section 2.1.

2.2.2 Incorporating Merton into the Market Model

To derive asset pricing implications of credit risk-induced skewness, we extend the classic Merton model by allowing the asset value to be affected by market risk. 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 $W^{\mathbb{P}}$. Thus, this specification accommodates systematic and idiosyncratic risk through $W^{\mathbb{P}}$ and $B^{\mathbb{P}}$, respectively.

As discussed above, equity is a European call option on the firm's assets and pays off the residual of asset value minus face value of debt at maturity, i.e. $E_T = \max(A_T - D, 0)$. Consistent with our discussion in Section 2.1, we denote the forward value of equity by $F_{t,T}$, which can be priced by the stochastic discount, i.e.

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

where $F_{T,T} = E_T$. 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 instead of the true beta (see 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 almost indistinguishable from 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, which the CAPM beta captures in its numerator, $Cov_0^{\mathbb{P}}(R, R_i)$. The left column in Figure 4 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 (upper vs lower panel). Taking a closer look at the CAPM beta components reveals that the firm's stock return volatility (middle column) exhibits the same patterns as the CAPM beta but that the correlation of firm stock returns and market returns (right column) decreases as leverage and asset volatility increase. In other words, the higher the firm's credit risk, the more idiosyncratic its equity returns as judged by the market correlation; nevertheless, the CAPM beta increases because of the firm's elevated equity volatility.

The left column in Figure 5 shows that also the firm's correlation with squared market returns (relative to the market returns' correlation with its squared returns) is a decreasing function of leverage and asset volatility. The right column illustrates the asset pricing implications by plotting the deviations of the skew-adjusted beta compared to the CAPM beta, where we measure these deviations as the ratio of true beta divided by CAPM beta minus one. The decreasing patterns suggest that differences in the skew-adjusted compared to the CAPM beta become more negative, which reflects that the firm becomes less connected to extreme market situations. 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. Figure 6 illustrates this decreasing premium return for the firm's coskewness by plotting the the difference between the skew-adjusted and the CAPM beta multiplied by the market risk premium, i.e. the difference in expected returns as derived in Equations (8) and (7), respectively. The right column of the same figure presents the associated values for the firm's ex-ante skewness. Ex-ante skewness exhibits exactly the same patterns as the compensation for coskewness: it is decreasing in leverage, asset volatility, and correlation with the market. This insight motivates our usage of firm equity-option implied measures of skewness in our empirical analysis of low risk anomalies.

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 its credit risk. Within the model, high credit risk is equivalent to more negative skewness, and we use these insights to explore the relation between skewness, equity returns, and risk measures that ignore higher moments of the return distribution. Next, we discuss the model's implications for low risk anomalies in more detail.

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 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 credit risk-induced skewness of firms' equity returns. Below, we examine the direct links between model implications and empirical low risk anomalies. Additionally, we discuss potential other sources of skewness.

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 (Fama and French, 2004). 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. They find that the BaB strategy generates significantly positive excess returns and present a model that rationalizes this finding by constrained investors bidding up high beta stocks.

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 (highest credit risk) but may not deliver excess returns for firms whose returns exhibit very little skewness (low credit risk).

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). We test this prediction in our empirical analysis and complement the results with idiosyncratic volatility relative to the Fama French factors as suggested by Ang et al. (2006).

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. This is consistent with the relation between equity returns and variance being U-shaped and the relation between variance and skewness illustrated in Figure 2: because variance increases as skewness becomes more negative, one expects high variance to predict low equity returns.

Other sources of skewness. Our theoretical framework features skewness through a credit risk channel, a link that has been confirmed empirically by numerous studies (see e.g. Hull et al., 2005; Carr and Wu, 2009, 2011). Previous research provides evidence that skewness may also be driven by, 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 alos discuss the interaction of disagreement and credit risk. As outlined above, our model does not account for such other sources of skewness and is limited to negative skewness induced by default risk. In this sense, it is an empirical question whether non-credit related skewness effects may confound the implications of our model when tested in the data. Our results suggest that this is not the case and that the empirical patterns that we document match the predictions of the model.

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 that of realized counterparts from equity returns, 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 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 and realized 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 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 below.

We now present the variance and skew measures suggested by Schneider and Trojani (2014). 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).[9] We

[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 difficulties in particular in the single-name market.

[9]The terminology *tradable* is motivated by the fact that quantities are computed from available option

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

$$VAR^{\mathbb{Q}}_{t,T} = \frac{2}{p_{t,T}} \left(\int_0^{F_{t,T}} \frac{\sqrt{\frac{K}{F_{t,T}}} P_{t,T}(K)}{K^2} dK + \int_{F_{t,T}}^{\infty} \frac{\sqrt{\frac{K}{F_{t,T}}} C_{t,T}(K)}{K^2} dK \right), \tag{11}$$

and

$$SKEW^{\mathbb{Q}}_{t,T} = \frac{1}{p_{t,T}} \left(\int_{F_{t,T}}^{\infty} \log\left(\frac{K}{F_{t,T}}\right) \frac{\sqrt{\frac{K}{F_{t,T}}} C_{t,T}(K)}{K^2} dK - \int_0^{F_{t,T}} \left(\log \frac{F_{t,T}}{K}\right) \frac{\sqrt{\frac{K}{F_{t,T}}} P_{t,T}(K)}{K^2} dK \right). \tag{12}$$

As can be seen from Equation (12), $SKEW^{\mathbb{Q}}_{t,T}$ can take positive or negative values, which illustrates that it is constructed precisely to measure deviations from put-call symmetry. In other words, 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. Under a continuum of option prices and dynamic updating of the option portfolios in Equations (11) and (12), realized variance ($VAR^{\mathbb{P}}_{n,t,T}$) and realized skewness ($SKEW^{\mathbb{P}}_{n,t,T}$) are given by

$$\begin{aligned} VAR^{\mathbb{P}}_{n,t,T} &:= 4 \sum_{i=1}^{n} \frac{F_{t_i,T}}{F_{t_{i-1},T}} + 1 - 2\sqrt{\frac{F_{t_i,T}}{F_{t_{i-1},T}}} \\ &= \sum_{i=1}^{n} \left(\log \frac{F_{t_i,T}}{F_{t_{i-1},T}}\right)^2 + O\left(\log \frac{F_{t_i,T}}{F_{t_{i-1},T}}\right)^3, \end{aligned} \tag{13}$$

data only. 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.

and

$$SKEW^{\mathbb{P}}_{n,t,T} := 4\sum_{i=1}^{n} \frac{F_{t_i,T}}{F_{t_{i-1},T}} - 1 - \sqrt{\frac{F_{t_i,T}}{F_{t_{i-1},T}}} \log\left(\frac{F_{t_i,T}}{F_{t_{i-1},T}}\right)$$
$$= \frac{1}{6}\sum_{i=1}^{n}\left(\log\frac{F_{t_i,T}}{F_{t_{i-1},T}}\right)^3 + O\left(\log\frac{F_{t_i,T}}{F_{t_{i-1},T}}\right)^4. \tag{14}$$

where n denotes the number of realized returns observed between t and T. Equations (13) and (14) show that the leading orders are quadratic and cubic in log returns for realized variance and realized skewness, respectively. Figure 7 illustrates the relation between one-step-ahead equity returns, realized variance, and realized skewness. Variance exhibits a U-shaped relation to underlying equity returns, i.e. high values of realized variance may be associated with either very positive or very negative stock returns. By contrast, skewness monotonically relates to equity returns, such that positive (negative) realized skewness coincides with positive (negative) equity returns.[10]

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 given in Equation (11). To measure ex-ante skewness $SKEW_{t,T}$, we use the option-implied skew from Equation (12) 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 (12), we can measure skewness effects net of variance effects.[11] Accordingly, our measure of realized skewness $RSKEW_{t,T}$ is given by standardizing the estimate of $SKEW^{\mathbb{P}}_{n,t,T}$, which we compute from daily data over the month that follows portfolio formation, i.e. n corresponds to the number

[10]Thus, to the extent that measures of ex-ante skewness contain information for future realized skewness they should also entail predictive ability for equity returns in the cross-section: if high (low) ex-ante skewness predicts high (low) realized skewness, equity returns should also be high (low).

[11]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.

of days in the respective month. Finally, we define skew risk premia as the difference between realized and ex-ante skewness, $SKRP_{t,T} = RSKEW_{t,T} - SKEW_{t,T}$.

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. 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

$$\hat{\beta_i^{TS}} = \hat{\rho}_i \frac{\hat{\sigma}_i}{\hat{\sigma_m}} \tag{15}$$

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 ($\hat{\beta}^{XS}$),

$$\hat{\beta}_i = w \times \hat{\beta_i^{ts}} + (1 - w) \times \hat{\beta}^{XS}, \tag{16}$$

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.

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 developed 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 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). Section 4.4 presents several robustness checks that corroborate our conclusions.

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 stock returns.

To assess the cross-sectional relation of implied skewness to the future equity return distribution, we first sort firms into equally-weighted 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.[12]

Panel B provides details on the positive relation between ex-ante skewness and subsequent equity returns for the 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

[12]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, the 5% and 95% quantiles given by 0.65 and 1.68, respectively.

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). More specifically, our results complement the mixed evidence on how ex-ante skew relates to subsequent equity returns (e.g. Conrad et al., 2013; Rehman and Vilkov, 2012). We show that the predictive relation is significantly positive and economically strong. In what follows, we show that understanding the link between ex-ante skew 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.[13] 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

[13] 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.

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 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 skew conveys return-relevant information not captured by betas and volatilities.

To explore the persistence of the relation between return 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 (which equals the HL return in Table 3). 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.

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.

4.3 The distress puzzle and skew risk premia

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. 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 the beta- and volatility-related low risk anomalies. Therefore, we discuss our findings from above and additional results related to skew risk premia in the context of the distress puzzle.

In our structural model, discussed in 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) written on the firm, is indeed reflected in prices of equity options (see e.g. Hull et al., 2005; Carr and Wu, 2009, 2011).[14] Therefore, it seems legitimate to recast the results on skew-sorted portfolios, presented above in Figure 8 and Table 1, as results from sorting firms into portfolios according to their credit risk. Recall that P_{10} is the low skew portfolio, i.e. the portfolio of firms whose OTM put options are most expensive relative to OTM call options. High put as compared to call prices reflect that these firms are the ones that face the highest credit risk. Correspondingly, the high skew portfolio P_1 contains firms with lowest credit risk. Thus, the results in Table 1 appear to reflect the distress puzzle, in that high credit risk firms earn significantly lower excess returns then low credit risk firms. In their concluding remarks, Campbell et al. (2008) speculate that accounting for skew preferences may help to understand the distress puzzle. Taken together, 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.

More recently, Friewald et al. (2014) provide a different perspective on the distress puzzle by arguing that the relation between credit risk and equity returns does not solely depend on either the risk-neutral or the real-world probability of a firm's default, but rather on the credit risk premium implied as a function of both of them. They find that credit risk premia implied

[14] 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.

by the term structure of CDS spreads are inversely related to equity returns, consistent with predictions derived from the model of Merton (1974).[15] Within our framework such credit risk premia directly correspond to skew risk premia, measured as the difference between realized skewness and ex-ante skewness.

Table 4 reports skew risk premia across firms for the portfolios sorted by ex-ante skewness. We find that skew risk premia increase from P_1 to P_{10}, suggesting that firms that earn low equity returns (firms with lowest ex-ante skew or equivalently highest credit risk) in turn generate high skew risk premia of around 10% (annualized, in P_{10}), while firms with high ex-ante skew (P_1) realize a skew risk premium of -11% p.a. Given the direct links between skewness, default risk, and CDS premia, our finding that equity returns (in Table 1) and skew risk premia (in Table 4) exhibit exactly opposing patterns, just corresponds to the finding of Friewald et al. (2014) that stock returns are inversely related to credit risk premia. In other words, the more negative skewness, the higher the risk premium (contained in option prices) that investors demand for providing insurance against downside risk.

These results illustrate from a different angle that credit risk by its very nature creates higher-moment risk that affects not only expected returns but the entire shape of the return distribution (as outlined in our theoretical discussion see Section 2). An interesting analogy is that compensation for corporate credit risk and compensation for crash risk in the aggregate market seem to follow similar channels; the latter has recently also been shown to be related to higher order preferences and (index) option-implied risk premia (e.g., Backus et al., 2011; Kozhan et al., 2013).

[15]The conceptual idea of Friewald et al. (2014) is that in the model of Merton (1974), where equity is a European call option on the firm's assets, a CDS contract can be represented as a put option on assets. Consequently, returns on stocks and CDS contracts have to be inversely related, and, given that returns on both instruments are driven by the same single source of risk, the return characteristics of one corporate claim represent relevant information for return characteristics of all other claims.

4.4 Discussion of additional results and robustness checks

This section presents further empirical results that corroborate our findings from the core analysis. We show that our conclusions remain unchanged and are robust to various changes to the double-sort procedure, such as changing the number of portfolios, using alternative return weighting schemes, and conducting conditional instead of unconditional portfolio double sorts.

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 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 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 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.

Demand for Lottery: Betting against $MAX5$. In a recent paper, Bali et al. (2014) 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 7 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.

5 Conclusion

This paper provides a novel perspective on beta- and 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 Coefficents for pricing kernel approximations

For a parsimonious analogous development of the arguments put forward in Section 2 yielding manageable closed-form expressions, we present here a market process driven by a geometric Brownian motion (GBM)

$$\frac{dM_{t,T}}{M_{t,T}} = \eta\, dt + \kappa\, dW_t^{\mathbb{P}}, \tag{A.1}$$

where the constant η denotes the instantaneous market return in excess of the risk-free rate and the constant κ the associated volatility. With the same power utility function as in the main text

$$\mathcal{M} := \frac{(R+1)^{-\gamma}}{\mathbb{E}_0^{\mathbb{P}}\left[(R+1)^{-\gamma}\right]} = \frac{(R+1)^{-\gamma}}{e^{1/2T\kappa^2(\gamma-\gamma^2)}}, \tag{A.2}$$

showing that in the GBM case the pricing kernel is measurable with respect to the market return R and that the market risk factor $(W^{\mathbb{P}})$ is the single source of risk in this economy. As a consequence the pricing kernel is identical as its projection $\mathbb{E}^{\mathbb{P}}\left[\mathcal{M} \mid R\right]$ and yields the CAPM in terms of log returns if $\log(R+1)$ and log asset returns are jointly normal.

The expressions for the coefficients a_1 and b_1 for the first-order approximation to the true pricing kernel in Section 2.1 are given by an expansion in R of the likelihood ratio $\mathcal{M} = \frac{d\mathbb{Q}_T}{d\mathbb{P}}$ in a L^2 space weighted with $d\mathbb{P}$. The functional form of the coefficients is as follows.

$$\begin{aligned}\mathcal{M}_1(R) = &\underbrace{-\frac{e^{-2\gamma\kappa^2T} - 2e^{\gamma\kappa^2(-T)} + e^{\kappa^2T}}{1-e^{\kappa^2T}}}_{a_1}\\ &+ \underbrace{-\frac{e^{-2\gamma\kappa^2T}\left(e^{\gamma\kappa^2T}-1\right)}{e^{\kappa^2T}-1}}_{b_1}\cdot R.\end{aligned} \tag{A.3}$$

For the second-order expansion, a_2, b_2, and c_2 are given by

$$\mathcal{M}_2(R) = \frac{e^{-3(2\gamma+1)\kappa^2 T}}{\left(e^{\kappa^2 T}-1\right)^2\left(e^{\kappa^2 T}+1\right)} \cdot \Big(e^{4(\gamma+1)\kappa^2 T} - e^{3(\gamma+1)\kappa^2 T} - 2e^{5(\gamma+1)\kappa^2 T} + e^{6(\gamma+1)\kappa^2 T} + e^{(2\gamma+1)\kappa^2 T}$$
$$+ 2e^{2(2\gamma+1)\kappa^2 T} - e^{(3\gamma+1)\kappa^2 T} - 2e^{(3\gamma+2)\kappa^2 T} + 2e^{(4\gamma+3)\kappa^2 T} + e^{(4\gamma+5)\kappa^2 T} - 2e^{(5\gamma+4)\kappa^2 T}\Big)$$
$$\underbrace{-\frac{e^{-3(2\gamma+1)\kappa^2 T}\left(e^{\gamma\kappa^2 T}-1\right)\left(-e^{3(\gamma+1)\kappa^2 T} + e^{4(\gamma+1)\kappa^2 T} + 2e^{(2\gamma+1)\kappa^2 T} - 3e^{(3\gamma+2)\kappa^2 T} + e^{(4\gamma+5)\kappa^2 T}\right)}{\left(e^{\kappa^2 T}-1\right)^2\left(e^{\kappa^2 T}+1\right)}}_{b_2} \cdot R$$
$$+ \underbrace{\frac{e^{-2(2\gamma+1)\kappa^2 T}\left(e^{\gamma\kappa^2 T}-1\right)\left(e^{(\gamma+1)\kappa^2 T}-1\right)}{\left(e^{\kappa^2 T}-1\right)^2\left(e^{\kappa^2 T}+1\right)}}_{c_2} \cdot R^2. \tag{A.4}$$

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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
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
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]
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]

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]
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]
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]
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 Andrews (1991). 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]
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]

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]
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]
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]
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: Skew risk premia

This Table summarizes skew risk premia across equally-weighted 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. We report skew risk premia (annualized in percent), measured as realized skewness minus ex-ante skewness, for individual portfolios as well as the $P_1 - P_{10}$ differential (HL). We 'raw skew risk premia' as well as 'alphas' of regressing skew risk premia on CAPM-, Fama-French three-, and four-factors. 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.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	HL
Excess return	-10.66^{***}	-1.95^{*}	-0.85	-0.32	0.65	0.65	1.25	1.93	3.16^{**}	9.80^{***}	-20.47^{***}
	[-7.57]	[-1.89]	[-0.84]	[-0.26]	[0.52]	[0.51]	[0.96]	[1.49]	[2.29]	[6.71]	[-9.66]
CAPM alpha	-11.59^{***}	-3.14^{***}	-2.02^{***}	-1.54^{*}	-0.62	-0.64	-0.08	0.62	1.82^{**}	8.60^{***}	-20.19^{***}
	[-8.26]	[-4.71]	[-3.10]	[-1.90]	[-0.82]	[-0.80]	[-0.09]	[0.72]	[2.01]	[9.08]	[-13.12]
FF3 alpha	-11.96^{***}	-3.49^{***}	-2.39^{***}	-2.02^{***}	-0.99	-1.09	-0.51	0.14	1.27	8.01^{***}	-19.97^{***}
	[-9.03]	[-5.80]	[-4.06]	[-2.90]	[-1.31]	[-1.41]	[-0.62]	[0.15]	[1.32]	[8.86]	[-12.28]
FF4 alpha	-11.65^{***}	-3.31^{***}	-2.28^{***}	-1.98^{***}	-0.93	-1.08	-0.56	0.09	1.23	7.88^{***}	-19.53^{***}
	[-9.61]	[-5.29]	[-3.76]	[-2.59]	[-1.15]	[-1.37]	[-0.64]	[0.09]	[1.27]	[9.69]	[-13.85]

Table 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]

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 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]

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]

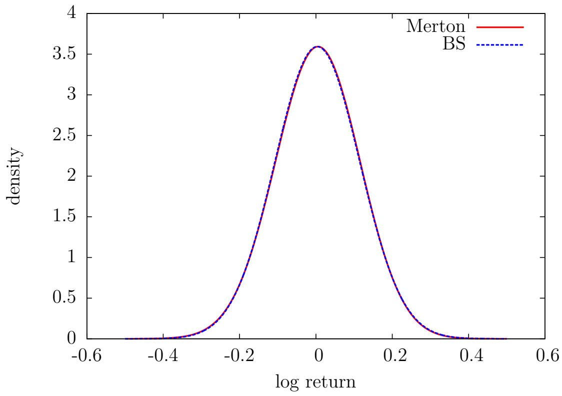
Panel D. Betting against ex-ante variance

	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]

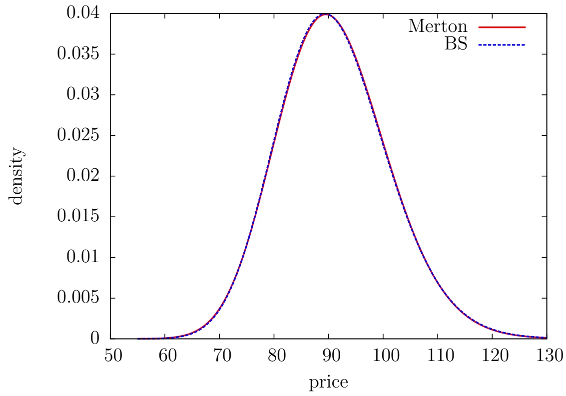
Table 7: Betting against $MAX5$ in skew-portfolios

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.

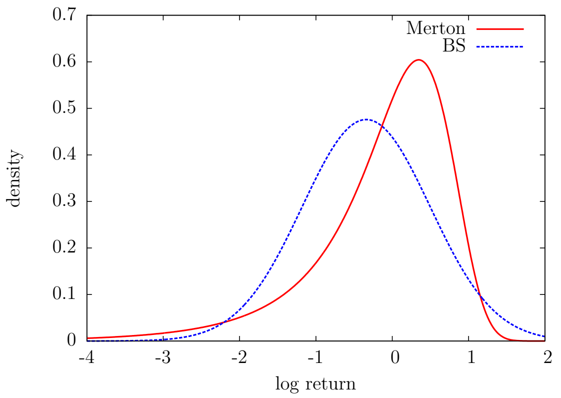
	Betting against $MAX5$		Betting against $MAX5$ in Skew Portfolios					
	5 Port.	10 Port	Skew-P_1	Skew-P_2	Skew-P_3	Skew-P_4	Skew-P_5	$P_5 - P_1$
Excess return	0.39	0.45	0.32	0.73	0.53	0.86	1.06**	0.75**
	[0.76]	[0.75]	[0.54]	[1.34]	[1.08]	[1.61]	[2.30]	[2.29]
CAPM alpha	1.03***	1.20**	1.03**	1.30***	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]



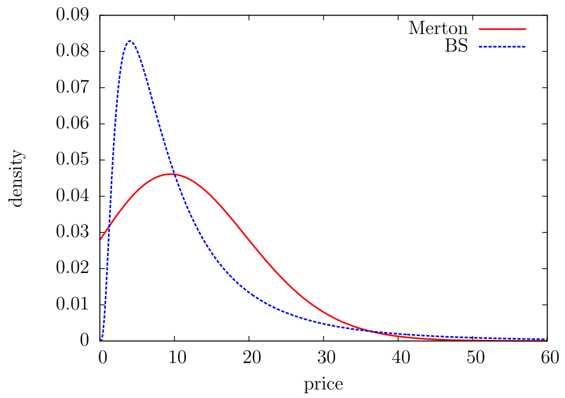
(a) Log Return – Low Leverage



(b) Price – Low Leverage

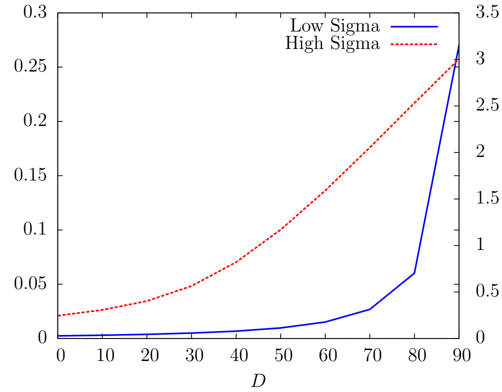


(c) Log Return – High Leverage

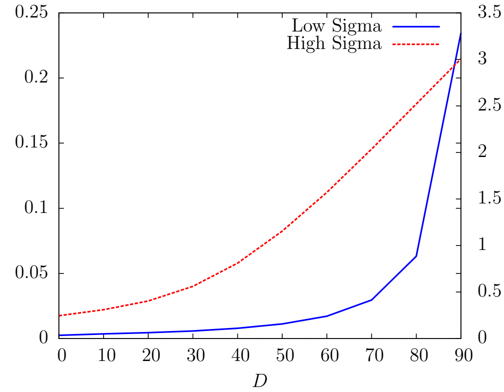


(d) Price – High Leverage

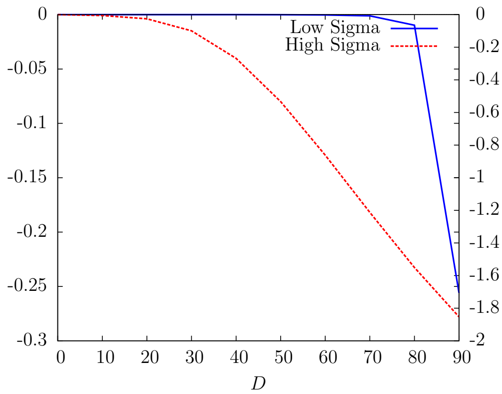
Figure 1: $\mathbb{Q}$ Densities of Merton-Implied Equity Returns and Prices: The figure plots Merton-implied and Black-Scholes-implied densities of equity log returns and prices. We present two examples: a low credit risk firm (panels (a) and (b)) and a high credit risk firm (panels (c) and (d)) which 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.



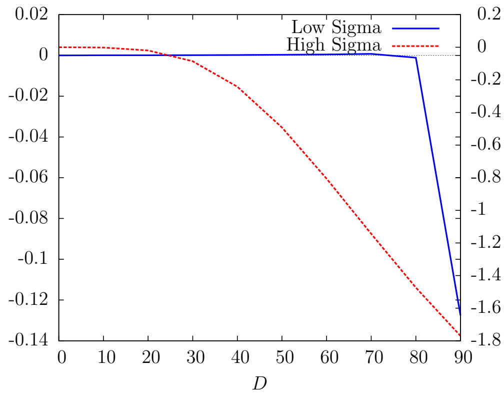
(a) Ex-ante Variance



(b) Expected Realized Variance

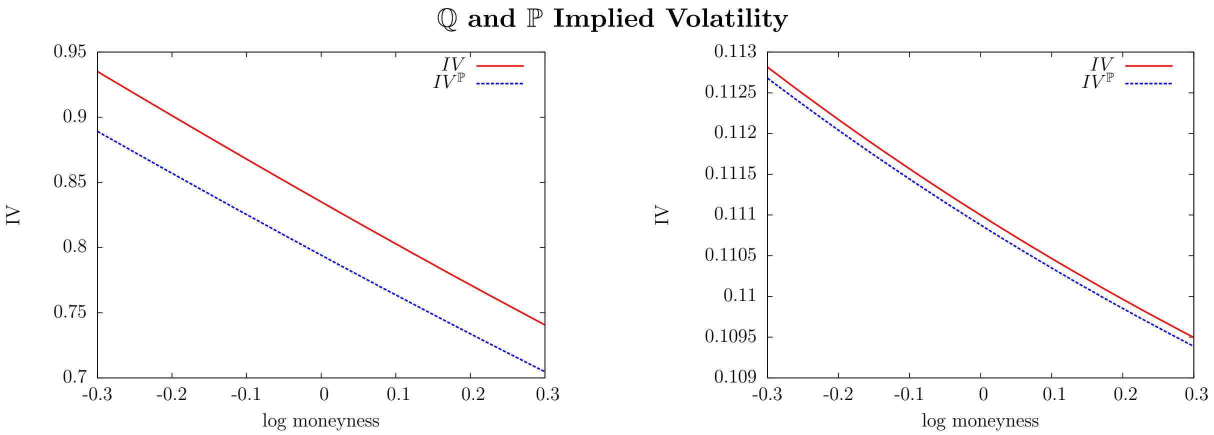


(c) Ex-ante Skewness

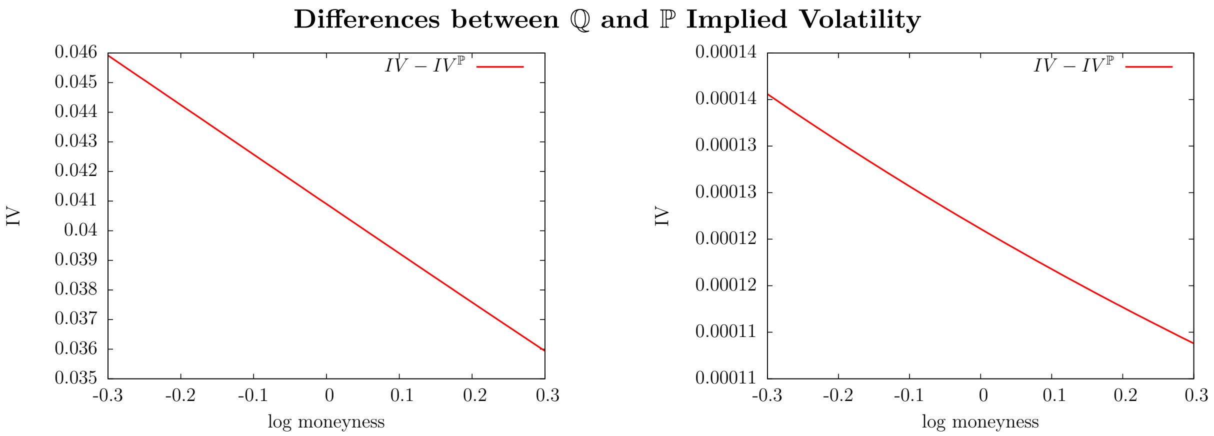


(d) Expected Realized Skewness

Figure 2: Ex-ante and realized variance and skewness: The figure plots ex-ante variance (a), realized variance (b), ex-ante skewness (c) and realized skewness (d) as a function of leverage (x-axis) in Merton's model. The plots are produced for a low asset volatility scenario (σ =5%, left y-axes) and a high asset volatility scenario (σ =50%, right y-axis). The remaining parameters are asset drift $\mu = 0.03$, value of assets today $V_0 = 100$, riskless rate $r = 0.01$, and $T = 1$.



(a) High Leverage **(b) Low Leverage**



(c) High Leverage **(d) Low Leverage**

Figure 3: Implied Volatilities The figure shows Black-Scholes-implied volatilities of options on Merton-implied equity. The high leverage examples differ from low-leverage examples through the face value of debt issued which is $D = 10$ (low leverage) and $D = 90$ (high leverage), respectively. The remaining parameters are time to maturity $T = 1$, value of assets today $V_0 = 100$, asset volatility $\sigma = 0.1$, riskless rate $r = 0.01$, and the drift rate of assets $\mu = 0.03$. Black-Scholes (BS) implied volatility IV is obtained in the standard way by equating the BS equity option price to the Merton equity option price via the parameter IV. For the $\mathbb{P}$ implied volatility $IV^{\mathbb{P}}$ we set the drift rate of equity under $\mathbb{P}, \mu_E^{\mathbb{P}} := \log(\mathbb{E}_0^{\mathbb{P}}[E_T]/(E_0 e^{rT})) \cdot 1/T$, where E_0 is the Merton-implied value of equity. We then introduce $\log E_t^{BS} \sim N(\log E_0 + (\mu^{\mathbb{P}} - \frac{1}{2}(IV^{\mathbb{P}})^2)t, \sqrt{t}IV^{\mathbb{P}})$ and equate the conditional expectations $\mathbb{E}_0^{\mathbb{P}}[\max(E_t - K, 0)] = \mathbb{E}_0^{\mathbb{P}}\left[\max(E_t^{BS} - K, 0)\right]$ for calls, and $\mathbb{E}_0^{\mathbb{P}}[\max(K - E_t, 0)] = \mathbb{E}_0^{\mathbb{P}}\left[\max(K - E_t^{BS}, 0)\right]$ for puts numerically via the parameter $IV^{\mathbb{P}}$ as a function of K.

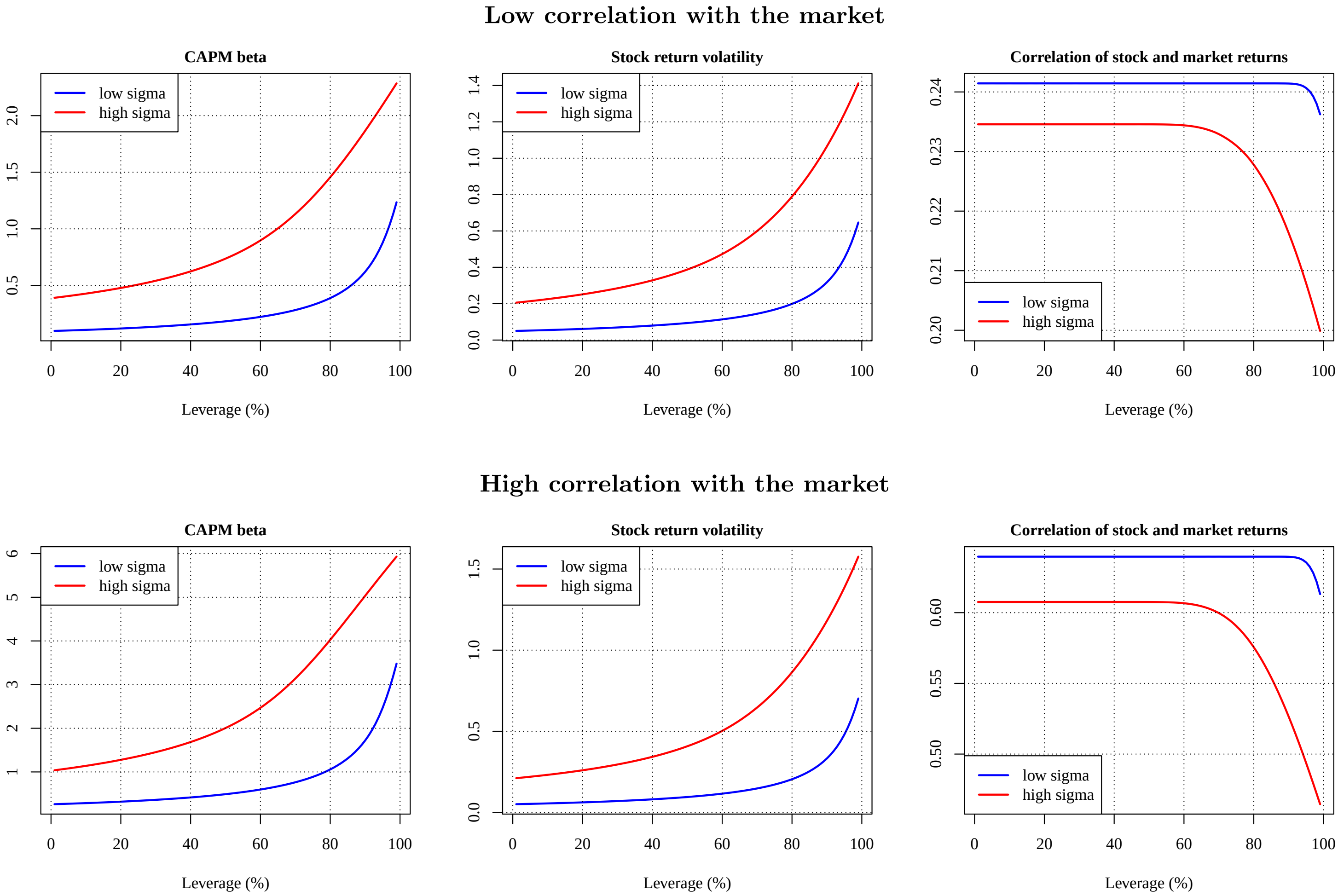


Figure 4: CAPM betas: The figure shows CAPM betas (left column), stock return volatilities (middle column), and correlations of stock returns with market returns (right column). In each plot, we consider a low asset volatility scenario (σ =5%) and a high asset volatility scenario (σ =20%). In the the top row, the firm has a low asset correlation with the market ($\rho = 30\%$), in the bottom row the firm has a high asset correlation with the market ($\rho = 80\%$), where the parameters refer to Equation (9). The parameters for the market from Equation (1) are $\xi = -0.85, \gamma = 2$ and for the stochastic market variance $\nu_0 = 0.025, \nu_1 = -1$, and volatility $\vartheta = 0.4$. This corresponds to an average market forward excess return of 5% p.a. Quantities are computed for a time horizon of 1 year.

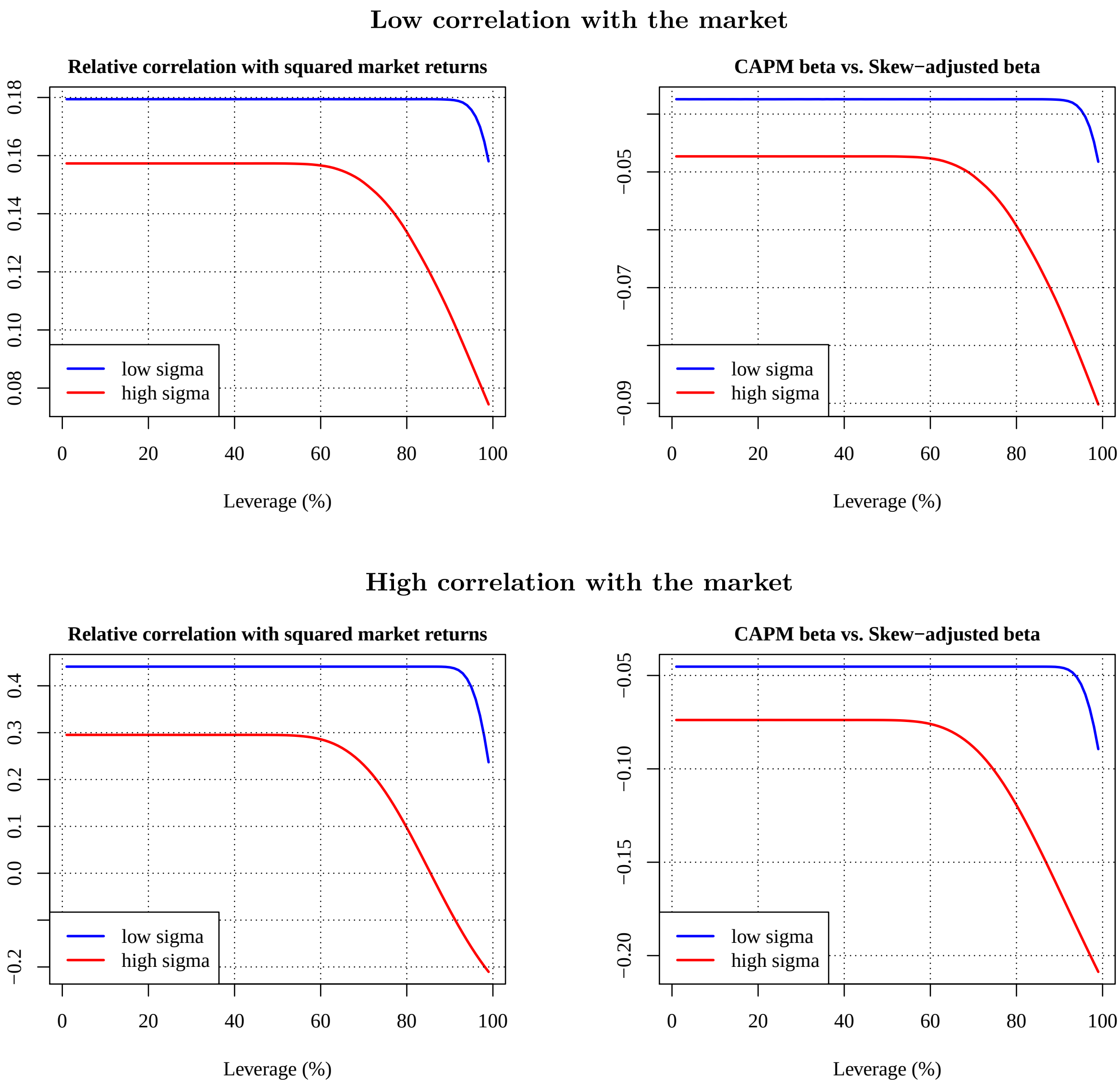


Figure 5: Coskewness and skew-adjusted betas: The left column plots the firm's coskewness, measured as the correlation of the firm's stock returns with squared market returns relative to the correlation of market with squared market returns. The right column illustrates deviations of the CAPM compared to the skew-adjusted beta. We plot the ratio of the skew-adjusted beta divided by the CAPM beta minus one. In each plot, we consider a low asset volatility scenario (σ =5%) and a high asset volatility scenario (σ =20%). In the the top row, the firm has a low asset correlation with the market ($\rho = 30\%$), in the bottom row the firm has a high asset correlation with the market ($\rho = 80\%$), where the parameters refer to Equation (9). The parameters for the market from Equation (1) are $\xi = -0.85, \gamma = 2$ and for the stochastic market variance $\nu_0 = 0.025, \nu_1 = -1$, and volatility $\vartheta = 0.4$. This corresponds to an average market forward excess return of 5% p.a. Quantities are computed for a time horizon of 1 year.

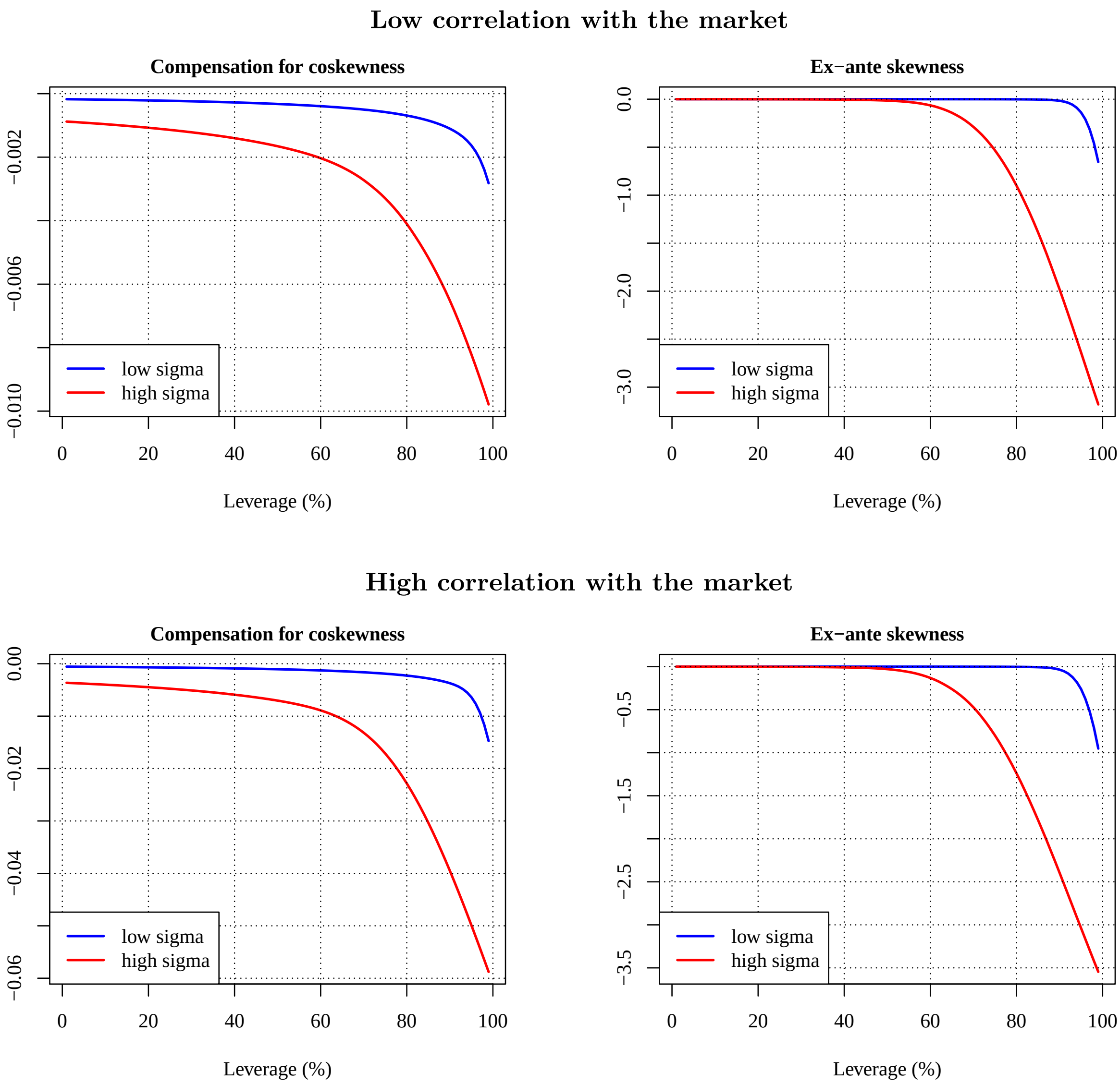
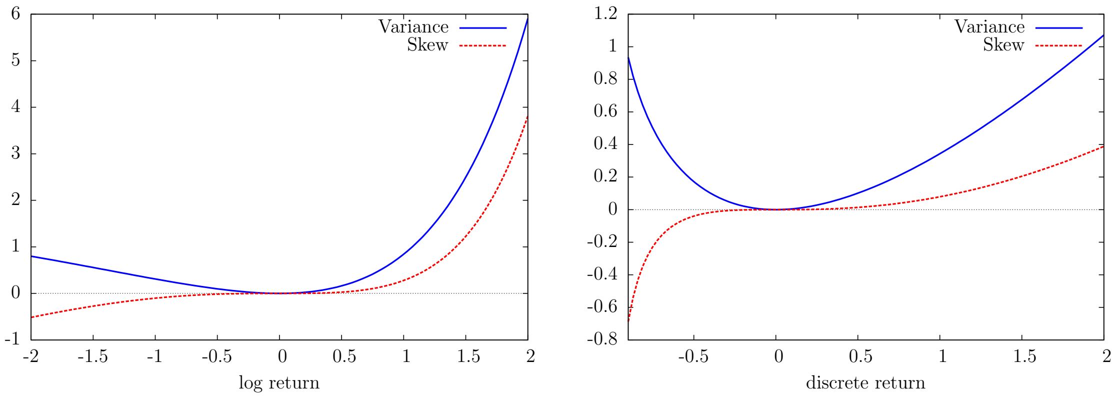
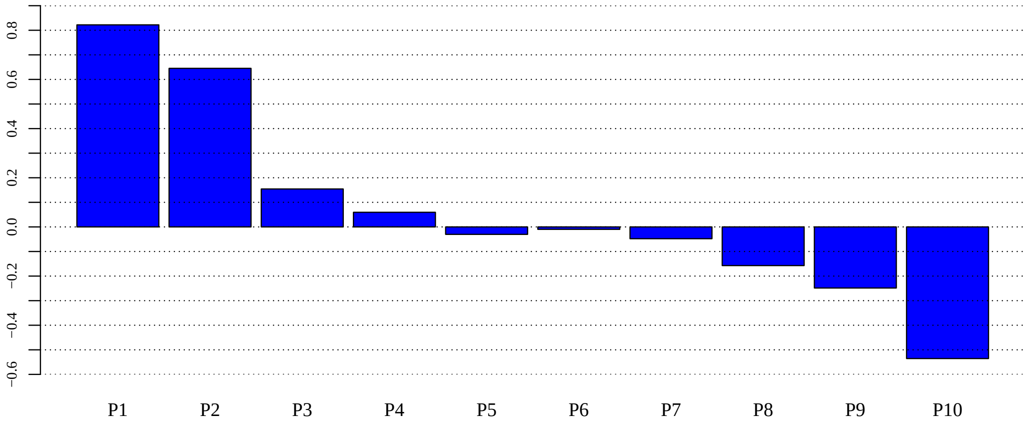


Figure 6: Ex-ante skewness and premium for coskewness: The left column plots the incremental expected equity return when accounting for co-skewness beyond CAPM covariance risk. We compute the compensation for co-skewness as (Skew-beta minus CAPM-beta) times the expected excess return on the market. The right column plots the firm's ex-ante skewness. In each plot, we consider a low asset volatility scenario (σ =5%) and a high asset volatility scenario (σ =20%). In the the top row, the firm has a low asset correlation with the market (ρ = 30%), in the bottom row the firm has a high asset correlation with the market (ρ = 80%), where the parameters refer to Equation (9). The parameters for the market from Equation (1) are $\xi = -0.85, \gamma = 2$ and for the stochastic market variance $\nu_0 = 0.025, \nu_1 = -1$, and volatility $\vartheta = 0.4$. This corresponds to an average market forward excess return of 5% p.a. Quantities are computed for a time horizon of 1 year.

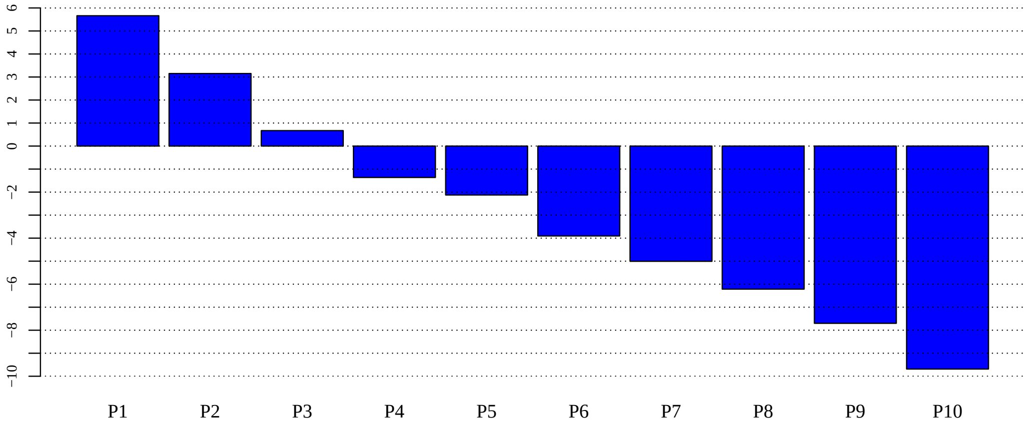


(a) Variance and Skew – Log Returns **(b) Variance and Skew – Discrete Returns**

Figure 7: Payoff Functions: The figure shows realized variance and realized skewness as a function of returns on the underlying forward. Panels (a) and (b) use log returns and discrete returns, respectively.

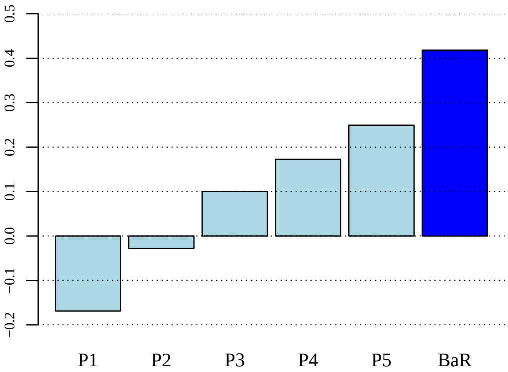


(a) Equity excess returns (monthly)

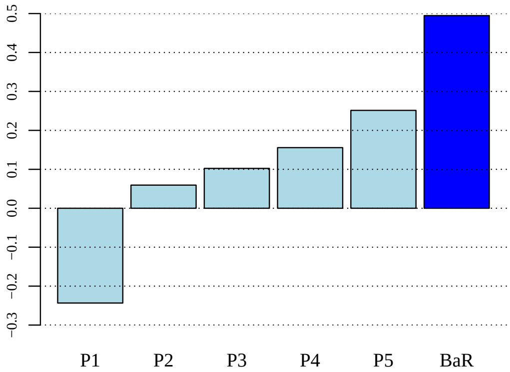


(b) Realized skewness (annualized)

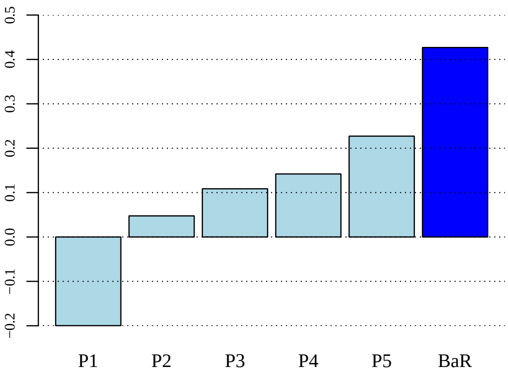
Figure 8: Ex-ante skewness and the distribution of future equity returns
At the end of every month, we sort firms into equally-weighted decile portfolios based on their ex-ante skewness. Portfolio P_1 (P_{10}) contains firms with highest (lowest) ex-ante skewness. For every portfolio, we compute equity 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.



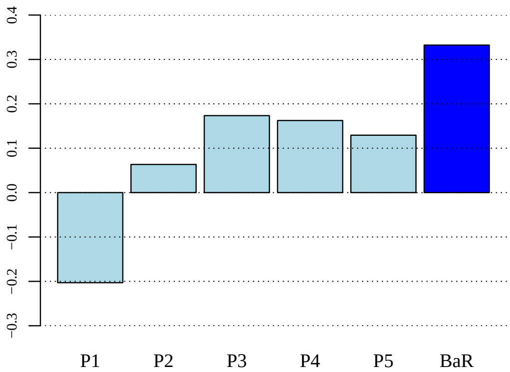
(a) Portfolios sorted on CAPM Beta



(b) Portfolios sorted on CAPM Idio. Vol.



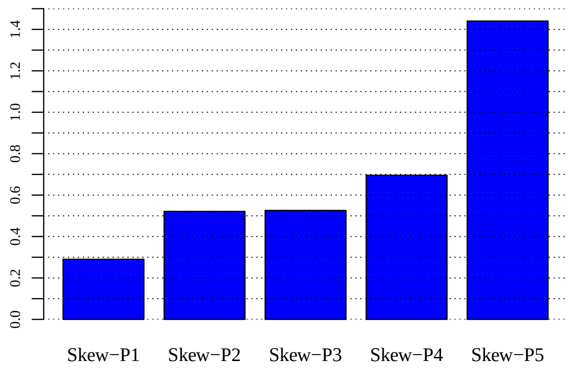
(c) Portfolios sorted on FF3 Idio Vola



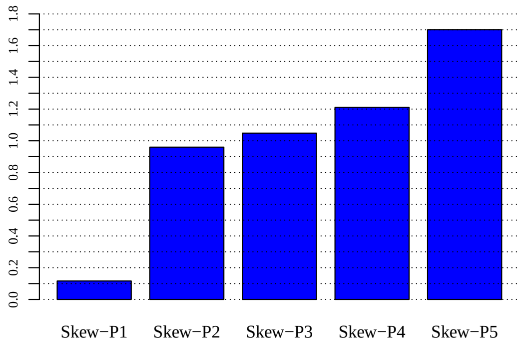
(d) Portfolios sorted on Variance

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

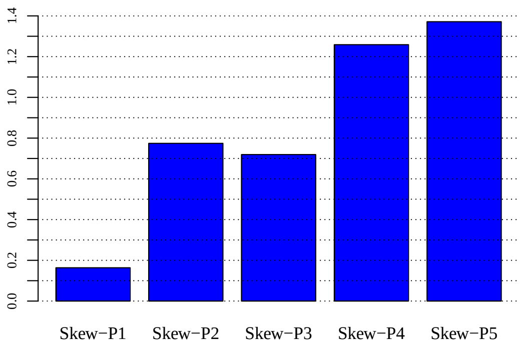
At the end of every month, we sort firms into equally-weighted quintile portfolios based on their CAPM beta (a), idiosyncratic volatility relative to the CAPM (b), idiosyncratic volatility relative to the Fama-French three-factor model (c), and ex-ante variance (d). Portfolio P_1 (P_5) contains firms 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.



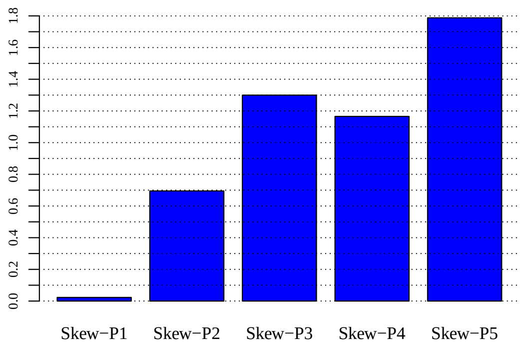
(a) Betting against CAPM Beta



(b) Betting against CAPM Idio. Vol.



(c) Betting against FF3 Idio Vola



(d) Betting against ex-ante variance

Figure 10: Betting against risk in skew portfolios

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.

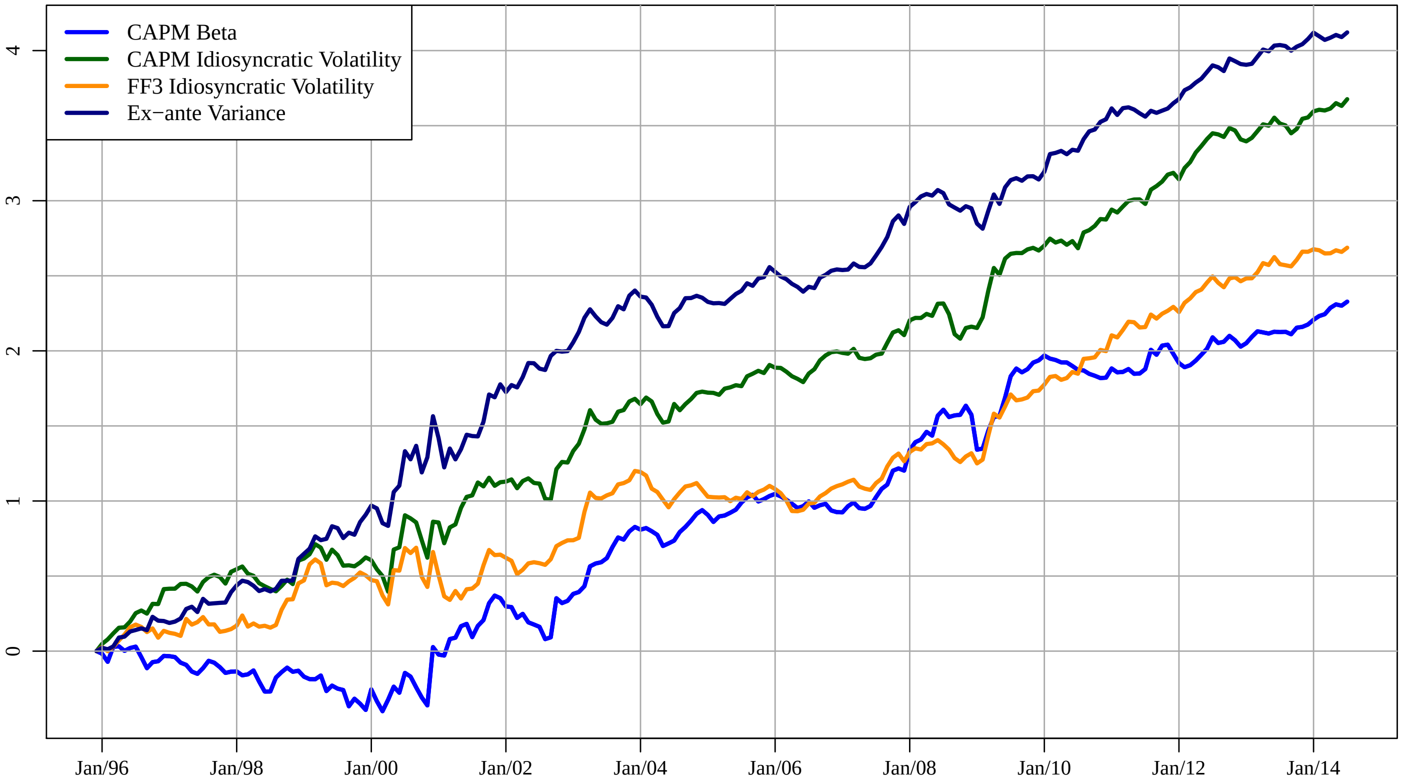


Figure 11: Cumulative returns of betting against beta/volatility in low vs high skew stocks
This figure plots the cumulative returns of betting against beta/volatility in low skew portfolios (Skew-P_5) in excess of betting against beta/volatility in high skew portfolios (Skew-P_1), resulting from unconditional 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.