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Bear beta[☆]

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A B S T R A C T

We test whether bear market risk, time variation in the probability of future bear market states, is priced. We construct an Arrow–Debreu security that pays off in bear market states (AD Bear) from traded Standard & Poor's (S&P) 500 index options and use its returns to measure bear market risk. We find that bear beta (exposure to bear market risk) has a strong relation with expected stock returns that is robust, persistent, and remains strong among liquid and large stocks. Historical bear beta also predicts future bear market risk exposure. We conclude that bear market risk is priced in the cross section of stock returns.

1. Introduction

This paper examines the pricing implications of bear market risk. We define bear market risk as time variation in the ex ante probability of future bear market states (i.e., states in which the market portfolio suffers a large loss). Exposure to bear market risk, that is, exposure to changes in the probability of future bear market states, is distinct from downside beta studied in Ang et al. (2006a) and jump

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beta studied in Cremers et al. (2015), which are sensitivities to present realizations of downside market states and jumps, respectively. Exposure to bear market risk is also distinct from volatility beta studied in Ang et al. (2006b), Chang et al. (2013), and Cremers et al. (2015) because bear market risk focuses on left-tail outcomes. The importance of these distinctions has been highlighted in theoretical work (Gabaix, 2012; Wachter, 2013) and numerous empirical time series studies (Santa-Clara and Yan, 2010; Bollerslev and Todorov, 2011b; Christoffersen et al., 2012; Andersen et al., 2015). We add to this body of work by examining the implications of bear market risk for the cross section of expected stock returns.

Our key innovation is to develop a measure of bear market risk. Motivated by Breeden and Litzenberger (1978), we construct an Arrow (1964) and Debreu (1959) portfolio (AD Bear) from traded Standard & Poor's (S&P) 500 index options. The AD Bear portfolio pays off $1 when the market at expiration is in a bear state.[1] Therefore, the price of the AD Bear portfolio is a forward-looking measure of the (risk-neutral) probability of future bear market states and the short-term AD Bear return reflects the change in this probability, i.e., bear market risk.[2] Our AD Bear portfolio is a bear spread position in S&P 500 index put options that is long an out-of-the-money (OTM) put and short a further OTM put. Bear spreads are frequently used as hedges against downside risk by institutional investors. The Chicago Mercantile Exchange (CME) maintains a separate order book for S&P 500 bear spread trades, which account for a substantial portion of S&P 500 option trading volume on the CME.[3] We take the loading on AD Bear excess returns from a regression of excess stock returns on market excess returns and AD Bear excess returns as our measure of a stock's bear market risk exposure, which we term "bear beta."[4]

Our main hypothesis is that bear market risk carries a negative price of risk. Intuitively, an increase in bear market risk reduces investors' utility and increases marginal utility. Therefore, assets with positive bear beta (i.e., assets that outperform when bear market risk increases) should earn low average returns because they pay off when marginal utility is high. Consistent with this prediction, the AD Bear portfolio generates a negative average excess return and negative alphas relative to the capital asset pricing model (CAPM) and other standard factor models.

Our focal tests examine the cross-sectional relation between future stock returns and bear beta. We find that the future returns of value-weighted decile portfolios sorted on bear beta are strongly decreasing across bear beta deciles. A zero-investment portfolio that is long the top bear beta decile portfolio and short the bottom decile portfolio generates an average return of about −1% per month, three-factor alpha of about −1.25% per month, and five-factor alpha of about −0.70% per month.

Additional tests further support a rational risk pricing interpretation of our results. We show that the spread in post-formation bear market risk exposure between the high- and low-bear beta portfolios is both economically and statistically significant. We also find that the negative cross-sectional relation between bear beta and future stock returns remains strong in samples containing only liquid stocks and large cap stocks (approximately the two thousand most liquid stocks and the one thousand largest stocks, respectively), for which arbitrage costs are minimal. Finally, bear beta predicts future stock returns for at least six months into the future.

The ability of bear beta to predict the cross section of future stock returns persists when controlling for other risk and characteristic variables known to be related to expected stock returns. We use bivariate portfolio analysis and Fama and MacBeth (1973, FM hereafter) regression analysis to control for CAPM beta, downside beta of Ang et al. (2006a), volatility index (VIX) beta and idiosyncratic volatility of Ang et al. (2006b), volatility and jump betas of Cremers et al. (2015), coskewness of Harvey and Siddique (2000), aggregate skewness beta of Chang et al. (2013), and tail beta of Kelly and Jiang (2014), as well as several firm characteristics. The results demonstrate that none of these measures subsumes the ability of bear beta to predict the cross section of future stock returns.

Our work makes two important contributions to the empirical asset pricing literature. First, we put forth AD Bear returns as a measure of bear market risk. AD Bear returns have the advantages of being economically intuitive, model-free, easy to measure, and tradable. Second, we show that stock-level exposure to bear market risk (bear beta) is a powerful determinant of the cross section of expected stock returns. Because bear beta captures stock return covariance with changes in the probability of future bear states, it does not rely on bear state realizations. Thus, bear beta is not subject to the potential peso problem arising from the fact that, in periods of prosperity, even the lowest returns perhaps do not represent bear states. Furthermore, because the probability of future bear market states varies continuously, we are able to estimate bear beta using the full set of data even though bear market

1 In our main specification, we define bear states to be states in which the market excess return is more than 1.5 standard deviations below zero and use the volatility index (VIX) as the measure of standard deviation.

2 The use of the short-term AD Bear portfolio return, instead of the hold-to-expiration return, is an important aspect of our analysis. The short-term return captures the change in the ex ante probability of future bear market states, and the hold-to-expiration return is completely determined by whether or not the market is in a bear state on the option expiration date.

3 See http://www.cmegroup.com/trading/equity-index/daily-index-option-spread-activity-report.html. Discussions with industry practitioners indicate that asset managers and insurance companies primarily use bear spreads as a hedge against equity market downturns. The reason institutions like spreads as opposed to just buying puts only is to reduce the price of the hedge. Carr and Wu (2011) implement a similar payoff structure at the firm level using single-stock options to capture default risk.

4 A simple put position also provides protection against bear market states. Our results are robust to using returns on an OTM put to capture bear market risk (see Section 6). We choose to use the AD Bear portfolio in our main tests for two reasons. First, the price of the AD Bear portfolio has a clear economic interpretation as the discounted risk-neutral probability of future bear market states, which makes it a useful vehicle for analyzing other state-contingent payoffs. Second, the price of the AD Bear portfolio is the difference between the prices of puts with different strikes and thus is less affected than a single put by forces, such as demand pressure (Garleanu et al., 2009), that could be unrelated to fundamental risks.

states occur infrequently. Consequently, bear beta is well measured and passes two of the most stringent tests of a covariance-based asset pricing model: It predicts both future returns and future risk exposure. These findings have practical implications for asset managers who need to allocate resources based on forward-looking forecasts of risk and expected returns. To our knowledge, bear beta is the first left-tail risk measure shown to satisfy these two criteria.

Our paper is related to several strands of literature. First, our empirical findings are consistent with the theoretical insight in Gabaix (2012) and Wachter (2013) that time variation in left-tail risk is critical in understanding asset returns. In Section 2, we use the Wachter (2013) model to convey the economic intuition underlying the AD Bear portfolio and show that bear market risk can be priced differently than CAPM market risk. In general, the economic concepts illustrated would hold in any asset pricing model that features time variation in the risk-neutral distribution of left-tail market events.

Second, our work builds on previous empirical research examining the implications of downside market risk exposure on the cross section of stock returns. Ang et al. (2006a) show that downside beta, the sensitivity of the stock's return to the market return when the market return is below its average, is positively related to the cross section of expected stock returns.[5] While the Ang et al. (2006a) downside beta measure relies on realizations of market down moves, our bear beta does not. To illustrate the difference, consider bear market states associated with the outbreak of war. Downside beta measures how a stock's price reacts to war. In contrast, even if a war does not materialize, as international tensions increase, the probability of a future war increases, as does bear market risk. Stock prices react to the increase in bear market risk, with some reacting more than the others. The price of the market portfolio also reacts because the market portfolio is composed of all stocks and is thus exposed to the same sources of risk that individual stocks are exposed to, including bear market risk. We control for this effect by including the market excess return in the regression used to calculate bear beta. Consequently, if a stock's reaction to bear market risk is completely captured by the stock's exposure to the market portfolio, this stock has a bear beta of zero. Bear betas are nonzero for stocks that have proportionally more or less exposure to bear market risk than the market portfolio.

Third, our paper is related to the line of research that investigates cross-sectional pricing implications of alternative measures of systematic risk exposure. Ang et al. (2006b) find that exposure to VIX is priced in the cross section of stock returns. Cremers et al. (2015) use returns on (delta-neutral and gamma-neutral) vega option portfolios to capture volatility risk and returns on (delta-neutral and vega-neutral) gamma option portfolios to capture jump risk, and they demonstrate that exposures to both risks are important determinants of the cross section of stock returns.[6] Bear beta is different from volatility beta because AD Bear tracks the cumulative probability of left-tail events, and volatility measures the standard deviation of the whole distribution. If the left tail of the market return distribution expands while the right tail shrinks, aggregate volatility remains unchanged while the cumulative probability of left-tail events increases. In such cases, the volatility portfolio has a zero return and the AD Bear portfolio has a positive return.[7] Bear beta differs from jump beta because jump beta captures exposure to large realized market movements, which drive the returns of the gamma portfolio, whereas bear beta does not rely on realizations of large market movements. Chang et al. (2013) find that innovations in the risk-neutral skewness of the market return is a priced risk factor. Our work differs from all of these previous studies in our focus on risk associated with future left-tail market outcomes. Volatility, skewness, and jump beta capture exposure to the full spectrum of the market return distribution. Nevertheless, volatility, jump, and skewness beta can capture some component of exposure to bear market risk. Empirically, while bear beta is correlated with these measures, including them as controls does not explain the bear beta effect. Our work is also related to Kelly and Jiang (2014), who find that stock-level sensitivity to a measure of aggregate left-tail risk explains the cross section of stock returns. However, our analysis differs from Kelly and Jiang (2014) in two important aspects. First, the aggregate tail measure in Kelly and Jiang (2014) is computed from large realized losses on individual stocks, which could capture different information than our index option-based measure. Second, Kelly and Jiang (2014) compute tail beta using regressions of stock returns on the lagged level of tail risk, whereas bear beta conforms to the traditional definition of risk exposure by measuring contemporaneous covariance between stock returns and risk factor innovations (i.e., AD Bear returns). We find that controlling for tail beta has little impact on the bear beta effect.

Finally, recent empirical time series work (Santa-Clara and Yan, 2010; Bollerslev and Todorov, 2011b; Andersen et al., 2015; Bollerslev et al., 2015; Martin, 2017) demonstrates that time series variation in tail risk and tail risk premia play an important role in understanding the time series of market returns.[8] We differ from the time

[5] Subsequent research follows this general theme. Bali et al. (2014) find that the left-tail return covariance between individual stocks predicts future stock returns. Lettau et al. (2014) show that market betas differ depending on the market state and that betas in bad market states are a key determinant of expected returns for many asset classes. Chabi-Yo et al. (2018) find that stocks that under-perform during crashes generate higher average returns. Farago and Tédongap (2018) extend the analysis in Ang et al. (2006a) and find that three disappointment-related factors are priced. Agarwal and Naik (2004) and Jurek and Stafford (2015) find that left-tail risk exposure explains a large portion of the time series of hedge fund returns.

[6] Other studies (e.g., Gao et al., 2018; Siriwardane, 2015) also investigate the pricing impact of jump risk.

[7] Santa-Clara and Yan (2010), Bollerslev and Todorov (2011b), Christoffersen et al. (2012), and Andersen et al. (2015) find that the time-varying ex ante probability of large negative jumps, which drives the returns of our AD Bear portfolio, is an economically distinct source of risk from stochastic volatility and has its own stochastic process.

[8] Other research shows related findings. Eraker (2004) finds that incorporating jumps helps explain the joint time series of market and index option returns. Pan (2002) uses the time series of index and index op-

series literature by demonstrating that exposure to bear market risk, which captures time variation in both left-tail risk and left-tail risk premia, is an important determinant of the cross section of expected stock returns. Our cross-sectional tests also demonstrate that exposure to bear market risk is priced differently from exposure to market risk and many other risk and characteristic variables. These findings are not evident from the time series literature.

The remainder of this paper proceeds as follows. In Section 2, we illustrate the economics underlying the AD Bear portfolio. Section 3 discusses the implementation of the AD Bear portfolio and examines its returns. In Section 4, we show that bear beta is an important determinant of the cross section of expected stock returns. Section 5 examines the pricing impact of bear beta after controlling for other known pricing effects. Section 6 demonstrates that our results are robust to alternative implementations of the AD Bear portfolio and bear beta. Section 7 concludes.

2. AD Bear and bear market risk in a model

To reinforce the economic intuition underlying our empirical design, we examine the theoretical relation between the pricing kernel, market risk, bear market risk, and AD Bear returns in a formal model. We choose the Wachter (2013) model to convey the intuition because Wachter (2013) explicitly models time variation in the probability of negative jumps and thus provides a natural setting to discuss the price of the AD Bear portfolio, which is the discounted risk-neutral probability of large market losses. Recent time series papers such as Bollerslev and Todorov (2011a,b) and Bollerslev et al. (2015) also use the Wachter (2013) model as a motivation for studying time variation in the probability of large market losses. However, the economic concepts illustrated would hold in any asset pricing model that features time variation in the risk-neutral distribution of left-tail market events.

In the Wachter (2013) model, aggregate consumption (C_t) follows a jump-diffusion process with time-varying jump intensity

$$dC_t = \mu C_{t^-} dt + \sigma C_{t^-} dB_t + (e^{Z_t} - 1) C_{t^-} dN_t, \tag{1}$$

where B_t is a standard Brownian motion and Z_t is a negative random variable with a time-invariant distribution that captures jump realizations. N_t is a Poisson process with time-varying intensity λ_t defined by

$$d\lambda_t = \kappa(\bar{\lambda} - \lambda_t) + \sigma_\lambda \sqrt{\lambda_t} dB_{\lambda,t}, \tag{2}$$

where $B_{\lambda,t}$ is a standard Brownian motion independent of both B_t and Z_t. Three independent sources of risk affect the consumption process: (1) B_t, a standard Brownian motion capturing continuous consumption shocks, (2) Z_t, the realized consumption jump at time t, and (3) λ_t, the time-varying intensity of future jumps. Because λ_t is the sole state variable that determines time variation in the probability of future bear market states, bear market risk in this model is the diffusive risk $dB_{\lambda,t}$. All asset returns in this model are determined by their exposures to these three sources of risk.

Table 1 presents the exposures of the stochastic discount factor or SDF (π_t), the price of the market porfolio (F_t), and the price of the AD Bear portfolio (X_t) to the three sources of risk. Derivations are provided in Section 1 in the Online Appendix. The exposures are derived using a first-order approximation, which facilitates the illustration of the economic intuition underlying AD Bear returns. The table conveys several economic takeaways relevant to our investigation.

First, the CAPM does not hold because SDF is not a linear function of the market return. As Table 1 shows, the sensitivities of the market return to both continuous consumption innovations (dB_t) and realized jumps (Z_t) are $-\phi/\gamma$ times the corresponding SDF sensitivities. However, the ratio of the sensitivities of the market return and the SDF to jump intensity innovations ($dB_{\lambda,t}$) is not equal to $-\phi/\gamma$ ($b_{F,\lambda}/b_{\pi,\lambda} \neq -\phi/\gamma$).

Second, we can measure a security's exposure to bear market risk by augmenting the CAPM with the excess returns of the AD Bear portfolio. As Table 1 shows, the AD Bear portfolio is proportionally more sensitive than the market portfolio to bear market risk. Therefore, one can hedge the AD Bear portfolio's exposure to market risk by investing one dollar in the AD Bear portfolio and Δ dollars in the market portfolio. This result motivates our use of a bivariate regression with the market excess return and the AD Bear excess return as independent variables to estimate a stock's bear beta. Ang et al. (2006b) and Cremers et al. (2015) also estimate exposures to option-based factors by augmenting the CAPM with one additional factor. This use of a bivariate regression should not be interpreted as suggesting that a two-factor model can price all assets. While our first-order approximation is sufficient to illustrate the effect of diffusive risk $dB_{\lambda,t}$, it perhaps does not account for higher-order effects driven by jump risk Z_t. Furthermore, the true return-generating process is likely more complicated than what is modeled in Wachter (2013), meaning that factors not included in the Wachter (2013) model could be needed to price all assets. Similar to Ang et al. (2006b) and Cremers et al. (2015), we address these concerns in our empirical tests by controlling for exposure to realized jumps, loadings on other risk factors, and various stock characteristics.

Finally, the model highlights the difference between our bear beta and other covariance measures such as the Cremers et al. (2015) jump beta measure and the Ang et al. (2006a) relative downside beta measure. Bear beta measures a stock's exposure to the diffusive risk $dB_{\lambda,t}$. In contrast, jump beta is designed to measure a stock's exposure to realized jumps Z_t. This is because Cremers et al. (2015) estimate jump beta by augmenting the CAPM with the excess returns of a delta-neutral and vega-neutral long gamma option jump portfolio, which is neutral to small movements but highly sensitive to large

tion returns to demonstrate that the jump risk premium covaries with market volatility in the time series. Broadie et al. (2007) find evidence of an unconditional jump risk premium in options, and Coval and Shumway (2001) find evidence of an unconditional left-tail risk premium in option returns.

Table 1
Sensitivities of market portfolio and AD Bear returns to three sources of fundamental risk.
The table shows the sensitivities of the stochastic discount factor (SDF, $\frac{d\pi_t}{\pi_{t-}}$), the market portfolio return ($\frac{dF_t}{F_{t-}}$), and the AD Bear portfolio return ($\frac{dX_t}{X_{t-}}$) to each of the three fundamental risks in the Wachter (2013) model derived using a first-order Taylor expansion. dB_t is a standard Brownian motion capturing continuous consumption shocks. Z_t is the realized consumption jump at time t. $dB_{\lambda,t}$ is the shock to the time-varying intensity of future jumps. $\Delta = e^{-\lambda_t \tau}\left(\sum_{n=0}^{\infty} \delta_n\right)\nu^{-1}$ is the ratio between the sensitivity of $\frac{dX_t}{X_{t-}}$ to dB_t and the sensitivity of $\frac{dF_t}{F_{t-}}$ to dB_t. Eqs. (1) and (2), and associated text, have more parameter definitions. Hedged AD Bear return is the return of a portfolio that invests one dollar in the AD Bear portfolio and hedges the market exposure by investing Δ dollars in the market portfolio. $b_{F,\lambda}$ is negative. γ, ϕ, $b_{\pi,\lambda}$, and $b_{X,\lambda}$ are positive.

Source of risk	SDF $\left(\frac{d\pi_t}{\pi_{t-}}\right)$	Market return $\left(\frac{dF_t}{F_{t-}}\right)$	AD Bear return $\left(\frac{dX_t}{X_{t-}}\right)$	Hedged AD Bear return $\left(\frac{dX_t}{X_{t-}}\right) + \Delta\left(\frac{dF_t}{F_{t-}}\right)$
dB_t	$-\gamma$	ϕ	$-\Delta\phi$	0
Z_t	$-\gamma Z_t$	ϕZ_t	$-\Delta\phi Z_t$	0
$dB_{\lambda,t}$	$b_{\pi,\lambda}$	$b_{F,\lambda}$	$-\Delta b_{F,\lambda} + b_{X,\lambda}$	$b_{X,\lambda}$

market returns arising from realized jumps.[9] Under the Wachter (2013) model, relative downside beta, a stock's differential exposure to the market factor in down versus up market states, also measures exposure to realized jumps because all risks other than the realized jumps Z_t in the model are symmetric in nature.

3. AD Bear portfolio

In this section, we describe the construction of the AD Bear portfolio and examine its returns.

3.1. Data

We gather data for S&P 500 index options traded on the Chicago Board Options Exchange (CBOE) expiring on the third Friday of each month, S&P 500 index levels, S&P 500 index dividend yields, VIX levels, and risk-free rates for the period from January 4, 1996 through August 31, 2015 from OptionMetrics (OM).[10] To ensure data quality, we remove options with bid prices of zero and options that violate simple arbitrage conditions, as indicated by a missing implied volatility in OM. We define the price of an option to be the average of the bid and offer prices and the dollar trading volume to be the number of contracts traded times the option price. The S&P 500 index forward price is taken to be $F = S_0 e^{(r-y)T}$, where S_0 is the closing level of the S&P 500 index, r is the continuously compounded risk-free rate, y is the dividend yield of the S&P 500 index, and T is the time to expiration.

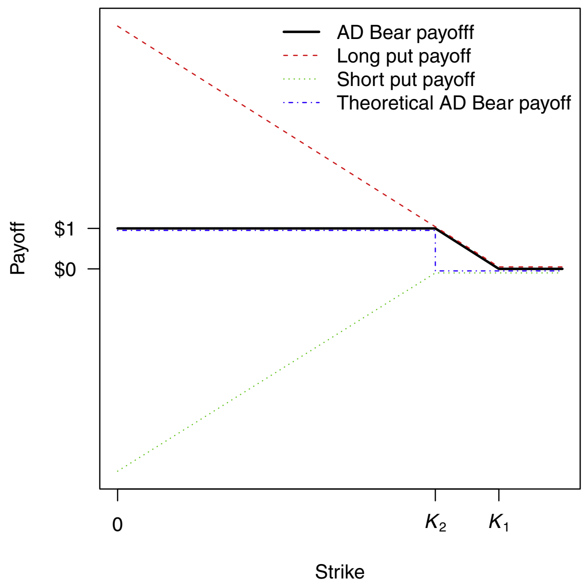

Fig. 1. Construction of AD Bear. The figure illustrates the construction of the AD Bear portfolio. The solid black line shows the payoff function of the AD Bear portfolio. The dashed red line shows the payoff function of the long put position. The dotted green line shows the payoff function of the short put position. The dash-dotted blue line shows the payoff function of the theoretical AD Bear portfolio. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Construction of AD Bear

Theoretically, the AD Bear portfolio generates a payoff of \$1 when the S&P 500 index level at expiration is in a bear state, defined as index levels below some value K_2 and zero otherwise. To approximate this payoff structure using traded options, we take a long position in a put option with strike price $K_1 > K_2$ and a short position in a put option with strike price K_2. Scaling both positions by $K_1 - K_2$, as shown in Fig. 1, the resulting AD Bear portfolio has a payoff at expiration of \$1 when the index level is below K_2 and zero when the index level is above K_1. The payoff linearly decreases from \$1 to zero for expiration

[9] Fig. 1 in Cremers et al. (2015) indicates a high correlation between their jump factor returns and realized jumps in the S&P 500 index. We also find, consistent with the close relation between jump beta and exposure to large market movements, a cross-sectional correlation of 0.56 between jump beta and the Harvey and Siddique (2000) coskewness measure calculated from one year of daily returns, which measures a stock's exposure to the squared market excess return.

[10] On January 31, 1997 and November 26, 1997, no VIX level is available. We set the VIX level on January 31, 1997 to 19.47, its closing value on January 30, 1997. Similarly, we set the VIX level on November 26, 1997 to 28.95, its closing value on November 25, 1997.

index levels between K_2 and K_1.[11] The price of the AD Bear portfolio, $P_{\text{AD Bear}}$, is therefore

$$P_{\text{AD Bear}} = \frac{P(K_1) - P(K_2)}{K_1 - K_2}, \tag{3}$$

where $P(K)$ is the price of a put option with strike price K.

K_2 defines the boundary of the bear region, which we set to be 1.5 standard deviations below the S&P 500 index forward price. This is equivalent to defining bear market states to be states in which the market excess return is more than 1.5 standard deviations below zero. We choose 1.5 standard deviations based on a trade-off between our objective of capturing the pricing of extreme left-tail states and the practical consideration that very far out-of-the-money put options are illiquid, making their pricing unreliable and frequently unavailable in the data. In Section 6, we demonstrate that the results are qualitatively the same with alternative definitions of the bear region.

We choose K_1 to be half a standard deviation above K_2 (i.e., one standard deviation below the forward price). Theoretically, the payoff function of our traded option portfolio converges to the theoretical AD Bear payoff function as $K_1 - K_2$ approaches zero. Empirically, as K_1 approaches K_2, the difference between $P(K_2)$ and $P(K_1)$ approaches zero, and the informational content of the price difference could be overwhelmed by noise induced by the bid-ask spread. Choosing $K_1 - K_2$ to be half a standard deviation balances these two considerations.

Following Jurek and Stafford (2015), we take the standard deviation of the market return to be the level of the VIX divided by one hundred multiplied by the square root of the time to expiration. Choosing VIX instead of a constant volatility as the measure of standard deviation ensures that each time the AD Bear portfolio is created, the targeted bear region has approximately constant risk-neutral probability.[12] Because the price of the AD Bear portfolio is simply the discounted risk-neutral probability of a bear market outcome, this means that, at the time of creation, the price of the AD Bear portfolio is approximately constant. Thus, while the AD Bear portfolio returns capture innovations in bear market risk, the price of the AD Bear portfolio at the time of creation does not reflect the level of bear market risk. In Section 6, we demonstrate that our results are robust when we use a constant standard deviation of 20%, which is close to the average VIX level of 21.02 during our sample period.

We make two empirical choices designed to reduce measurement error and enhance our ability to capture bear market risk. First, because a traded option with the exact targeted strike is unlikely to exist, we take $P(K_1)$ and $P(K_2)$ to be the dollar trading volume-weighted average price of puts with strikes within a 0.25 standard deviation range of the target strike (K_1 or K_2). We define

$$P(K_1) = \sum_{K \in \left[Fe^{-1.25 \frac{VIX}{100}\sqrt{T}},\, Fe^{-0.75 \frac{VIX}{100}\sqrt{T}}\right]} P(K)w(K) \tag{4}$$

and

$$P(K_2) = \sum_{K \in \left[Fe^{-1.75 \frac{VIX}{100}\sqrt{T}},\, Fe^{-1.25 \frac{VIX}{100}\sqrt{T}}\right]} P(K)w(K), \tag{5}$$

where the summation is taken over all traded puts with strikes in the indicated range and $w(K)$ is the dollar trading volume of the put with strike K scaled by the total dollar trading volume of all puts in the summation. Taking the volume-weighted average put price over a range of strikes increases the informativeness of the AD Bear portfolio price by putting more weight on liquid options whose prices are likely to be more reflective of true option value and less subject to noise induced by the bid-ask spread. Robustness tests discussed in Section 6 show that the results are nearly unchanged when equal weights are used.

Second, motivated by liquidity considerations, we create the AD Bear portfolio using one-month options, which are defined as options that expire in the calendar month subsequent to the month in which the portfolio is created.[13] Robustness tests discussed in Section 6 show that the results are qualitatively the same when two-month options are used.

3.3. AD Bear portfolio returns

For each trading day from January 4, 1996 through August 24, 2015, we create the AD Bear portfolio. We calculate the buy-and-hold return of this AD Bear portfolio over the next five trading days (one calendar week except when there is a holiday). The choice to use a five-day return is based on a trade-off between theory and practical considerations. Our theoretical motivation is based on instantaneous returns, which leads us to use a return period as short as possible. However, bear betas computed using short-term returns can be influenced by measurement noise related to the bid-ask spread and nonsynchronous trading in the stock and option markets. Using five-day returns is a reasonable balance between these two considerations.[14] We subtract the five-day risk-free rate from the

[11] An alternative approach to measuring the price of the AD Bear portfolio would be to estimate the cumulative risk-neutral density evaluated at K_2 by using an interpolation technique to generate a continuum of option prices (see Figlewski, 2010). This alternative approach requires making assumptions about the functional form of the relation between strike prices and option prices. Our approach alleviates the need to make such assumptions and has the added benefit that the AD Bear portfolio is easily constructed from traded options.

[12] Our bear region corresponds to approximately the worst 6.7% of market states under the assumption of log-normally distributed returns. If we had set the bear region boundary to a constant percentage below the forward price, e.g., an 8.3% loss (or, equivalently, 1.5 standard deviations below the forward price when volatility is 20%), the bear region would correspond to relatively low probability left-tail events when volatility is low (e.g., when volatility is 10%, an 8.3% loss corresponds to a 3 standard deviation move) and to relatively high probability events when volatility is high (e.g., when volatility is 60%, an 8.3% loss corresponds to a 0.5 standard deviation move).

[13] The use of one-month options is consistent with previous research (Chang et al., 2013; Cremers et al., 2015; Jurek and Stafford, 2015). In unreported analyses, we find that one-month options are more liquid than options with longer times to expiration.

[14] Previous research has used similar techniques to combat such noise in the data. To minimize the effect of nonsynchronous trading (Scholes and Williams, 1977; Dimson, 1979), Frazzini and Pedersen (2014) use overlapping three-day stock returns to compute the correlation between

Table 2
Summary statistics for AD Bear portfolio and factor returns.
The table presents summary statistics for the five-day excess returns of the AD Bear portfolio and standard risk factors. The unscaled AD Bear excess returns [AD Bear (unscaled)] are the actual excess returns generated by the AD Bear portfolio. The scaled (AD Bear) excess returns are the unscaled excess returns divided by 28.87836. The scaling factor 28.87836 is chosen so that the standard deviation of the scaled AD Bear excess returns is equal to the standard deviation of the market (MKT) factor returns. The five-day excess returns of the market (MKT) factor, the size (SMB, small minus big) and value (HML, high minus low) factors of Fama and French (1993), the momentum (MOM) factor of Carhart (1997), the size (ME, market equity), profitability (ROE, return on equity), and investment (I/A, investment to assets) factors from the Q-factor model of Hou et al. (2015), and the size (SMB_5), profitability (RMW, robust minus weak), and investment (CMA, conservative minus aggressive) factor from the five-factor model of Fama and French (2015) are calculated by first compounding the daily gross returns of the factors over a five-day period and then subtracting the contemporaneous five-day risk-free rate. The table presents the mean, standard deviation, skewness, minimum value, median value, 95th percentile value, 99th percentile value, and maximum value for the daily five-day overlapping excess returns of the AD Bear portfolio and each of the factors. The returns cover portfolio formation dates (return dates) from January 4, 1996 (January 11, 1996) through August 24, 2015 (August 31, 2015).

Factor	Mean	Standard deviation	Skewness	Minimum	Median	95th percentile	99th percentile	Maximum
AD Bear (unscaled)	−8.12	74.72	2.81	−98.31	−28.48	131.60	269.91	999.68
AD Bear	−0.28	2.59	2.81	−3.40	−0.99	4.56	9.35	34.62
MKT	0.15	2.59	−0.49	−18.43	0.31	3.79	6.53	19.49
SMB	0.04	1.46	−0.48	−12.19	0.08	2.14	3.89	7.52
HML	0.05	1.52	0.54	−8.29	0.02	2.32	5.17	12.47
MOM	0.14	2.45	−0.93	−16.45	0.25	3.59	6.48	14.21
ME	0.07	1.46	−0.34	−11.12	0.10	2.19	3.93	7.79
ROE	0.11	1.27	0.10	−6.36	0.13	2.03	3.93	10.14
I/A	0.06	1.03	0.65	−5.66	0.01	1.70	3.09	8.61
SMB_5	0.05	1.41	−0.42	−11.81	0.09	2.09	3.70	7.36
RMW	0.09	1.21	0.75	−7.09	0.06	1.89	3.89	9.88
CMA	0.06	1.04	0.81	−5.15	−0.01	1.83	3.27	8.99

five-day buy-and-hold AD Bear return to get the AD Bear portfolio excess return for the five day period ending on day d, which we denote $R_{\text{AD Bear}, d}$.[15] The result is a time series of overlapping five-day AD Bear portfolio excess returns for the period from January 11, 1996 through August 31, 2015.[16]

Table 2 presents summary statistics for the daily five-day overlapping excess returns of the AD Bear portfolio. Because the AD Bear portfolio pays off in high marginal utility states, we expect it to earn a negative average excess return. The row labeled "AD Bear (unscaled)" shows that AD Bear generates an average excess return of −8.12% per five-day period, with a standard deviation of 74.72%. The large magnitude of the average AD Bear excess return reflects the leverage embedded in options. To facilitate comparison with other factors, for the remainder of this paper, we scale the AD Bear excess returns by 28.87836 so that the standard deviation of the scaled AD Bear excess returns is equal to that of the market excess returns. The row labeled "AD Bear" presents summary statistics for the scaled AD Bear portfolio excess returns. The AD Bear portfolio generates a scaled average excess return of −0.28% per five-day period with a standard deviation of 2.59. As Table 3 shows, the average AD Bear excess return is highly significant with a Newey and West (1987, NW hereafter)–adjusted t-statistic of −3.89. The distribution of AD Bear excess returns exhibits large positive skewness of 2.81.

For comparison, the remainder of Table 2 presents summary statistics for the daily five-day excess returns of the market (MKT) factor, the size (SMB, small minus big) and value (HML, high minus low) factors of Fama and French (1993), the momentum (MOM) factor of Carhart (1997), the size (ME, market equity), profitability (ROE, return on equity), and investment (I/A, investment-to-assets) factors from the Q-factor model of Hou et al. (2015), and the size (SMB_5), profitability (RMW, robust minus weak), and investment (CMA, conservative minus aggressive) factors from the five-factor model of Fama and French (2015).[17]

stocks returns and market returns. Hou and Moskowitz (2005) explicitly mention measurement error induced by the bid-ask spread and nonsynchronous trading as a reason to study weekly returns, instead of daily or intradaily returns. In robustness tests presented in Section 6, we show that the results using four-day AD Bear returns are very similar to the results using five-day AD Bear returns. Consistent with the notion that very short-term returns are more influenced by measurement issues, the results get weaker as we progress to using three-day, two-day, and one-day AD Bear returns.

[15] Daily risk-free security return data are gathered from Kenneth French's data library, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[16] If insufficient data are available to calculate the AD Bear return (see Jurek and Stafford, 2015), we consider the return for the given five-day period to be missing. There are 4,910 valid returns out of 4,944 days during the sample period. Because the AD Bear portfolio is constructed from options, its returns reflect both changes in the physical probability of a future bear market state and changes in the risk premium associated with bear market states. Similar to Ang et al. (2006b), Chang et al. (2013), and Cremers et al. (2015), we do not attempt to differentiate between these two sources of variation. Differentiating between changes in risk premia and changes in physical probability would require specifying a return-generating process, which can introduce specification error into the analysis. A benefit of our approach is that it is model-free.

[17] MKT, SMB, HML, MOM, SMB_5, RMW, and CMA factor return data are gathered from Kenneth French's data library. We thank Lu Zhang for providing the ME, ROE, and I/A factor returns. The five-day excess factor returns are calculated as the daily factor gross return, compounded over the given five-day period, minus the five-day gross compounded return of the risk-free security.

Table 3
Factor analysis of AD Bear portfolio returns.
The table presents the results of time series regressions of AD Bear portfolio excess returns on standard factors. The table shows the intercept coefficient (Excess return or α), slope coefficients (β), and adjusted R-squared (Adj. R^2). t-statistics, adjusted following Newey and West (1987) using 22 lags, testing the null hypothesis of a zero intercept or slope coefficient, are shown in parentheses below the corresponding coefficients. The regressions include the 4,910 valid five-day AD Bear excess return observations during the period from January 11, 1996 through August 31, 2015. CAPM indicates capital asset pricing model; FF3 indicates Fama and French (1993) three-factor model; FFC indicates Fama and French (1993) and Carhart (1997) four-factor model; Q indicates Hou et al. (2015) Q-factor model; FF5 indicates Fama and French (2015) five-factor model.

Value	Excess return	CAPM	FF3	FFC	Q	FF5
Excess return or α	−0.28	−0.15	−0.16	−0.14	−0.13	−0.13
	(−3.89)	(−3.99)	(−4.02)	(−3.37)	(−3.23)	(−3.09)
β_{MKT}		−0.81	−0.81	−0.85	−0.85	−0.87
		(−18.84)	(−18.44)	(−20.67)	(−18.37)	(−19.67)
β_{SMB}			0.06	0.07		
			(1.93)	(2.20)		
β_{HML}			0.05	−0.00		0.16
			(1.01)	(−0.09)		(2.89)
β_{MOM}				−0.11		
				(−4.48)		
β_{ME}					0.04	
					(1.23)	
β_{ROE}					−0.14	
					(−2.92)	
$\beta_{I/A}$					−0.06	
					(−1.20)	
β_{SMB_5}						0.02
						(0.65)
β_{RMW}						−0.16
						(−3.49)
β_{CMA}						−0.25
						(−4.05)
Adj. R^2	0.00%	65.32%	65.47%	66.41%	65.88%	66.39%

The mean five-day excess returns of the factors range from 0.04% for the SMB factor to 0.15% for the MKT factor.

3.4. Factor analysis of AD Bear returns

We next examine whether the average return of the AD Bear portfolio can be explained by exposure to standard risk factors. We measure AD Bear's risk exposures by regressing five-day AD Bear excess returns, $R_{\text{AD Bear},d}$, on contemporaneous risk factor returns, $\mathbf{F_d}$. The regression specification is

$$R_{\text{AD Bear},d} = \alpha + \beta' \mathbf{F_d} + \epsilon_d. \tag{6}$$

The standard risk factors we use are returns of zero-investment portfolios. The average returns of these portfolios capture the factor risk premia. Therefore, α in regression Eq. (6) measures the average return of the AD Bear portfolio that is not compensation for exposure to the risk factors considered. AD Bear has positive exposure to bear market risk and bear market risk is predicted to carry a negative premium. If bear market risk is distinct from previously identified factors, then our hypothesis predicts that AD Bear should generate negative alpha relative to standard factor models. Our first factor analysis examines whether the premium earned by the AD Bear portfolio is explained by exposure to CAPM market risk. Table 3 shows that AD Bear has a strong negative exposure to the market factor of −0.81, consistent with its negative delta exposure. The market factor explains 65% of the total variation in AD Bear excess returns. Despite this strong exposure, the average AD Bear excess return cannot be fully explained by market factor exposure. AD Bear's alpha relative to the CAPM is −0.15% per five days, highly significant with a t-statistic of −3.99. This is our first indication of a negative price of bear market risk.

We then test whether AD Bear's CAPM alpha can be explained by other standard risk factors. Table 3 shows that AD Bear produces alpha of −0.16% per five day period (t-statistic = −4.02) relative to the Fama and French (1993) model (FF3) that contains MKT, SMB, and HML and alpha of −0.14% per five day period (t-statistic of −3.37) relative to the four-factor model of Fama and French (1993) and Carhart (1997) (FFC) that contains MKT, SMB, HML, and MOM. AD Bear's alpha relative to the Q-factor model of Hou et al. (2015) (Q) that contains MKT, ME, ROE, and I/A is −0.13% per five-day period (t-statistic of −3.23). Finally, AD Bear generates alpha of −0.13% (t-statistic = −3.09) per five-day period relative to the Fama and French (2015) five-factor model (FF5), which contains MKT, SMB_5, HML, RMW, and CMA. The results indicate that the premium earned by AD Bear cannot be fully explained by these risk factor models. Augmenting the CAPM with additional risk factors has a negligible impact on the R^2.

The factor analysis of AD Bear portfolio returns has a few caveats. First, the abnormal returns indicated by the factor models perhaps are not easily obtained in practice because trading the AD Bear portfolio can incur substantial transaction costs. Second, as discussed in Broadie et al. (2009), there are econometric issues associated with subjecting option returns to standard linear factor models commonly used to analyze stock returns. We therefore view AD Bear's significant alphas as consistent with our hypothesis that bear market risk carries a negative risk premium but do not draw any strong conclusions from these tests. Our main tests of this hypothesis, presented in the remainder of this paper, examine the cross section of stock returns and therefore are not susceptible to these concerns.

4. Bear beta and expected stock returns

If the negative alpha of the AD Bear portfolio is compensation for exposure to bear market risk, stock-level sensitivity to bear market risk should exhibit a negative cross-sectional relation with expected stock returns. In this section, we test this hypothesis.

4.1. Bear beta

We estimate bear beta for each stock i at the end of each month t by running a time series regression of excess stock returns on the excess market return (MKT) and the scaled excess return of the AD Bear portfolio. The regression specification is

$$R_{i,d} = \beta_0 + \beta_i^{\mathrm{MKT}}\mathrm{MKT}_d + \beta_i^{\mathrm{BEAR}}R_{\mathrm{AD\ Bear},d} + \epsilon_{i,d}, \tag{7}$$

where $R_{i,d}$ is the excess return of stock i over the the five–trading day period ending at the close of day d, MKT_d is the contemporaneous market excess return, and $R_{\mathrm{AD\ Bear},\,d}$ is the contemporaneous AD Bear excess return. The AD Bear portfolio is formed at the close of trading day $d-5$ and held until the close of day d. All returns are calculated over this same period. Stock return data are from the Center for Research in Security Prices. The regression uses overlapping returns for five-day periods ending in months $t-11$ through t, inclusive. We require at least 180 valid observations to estimate the regression. To minimize estimation error, we follow Fama and French (1997) and adjust the ordinary least squares (OLS) coefficient using a Bayes shrinkage method. For each stock i and month t, we run the regression specified in Eq. (7) and let $\beta_{\mathrm{OLS},i,t}^{\mathrm{BEAR}}$ be the estimated coefficient on $R_{\mathrm{AD\ Bear},d}$ and $\sigma_{\mathrm{OLS},i,t}^2$ be the variance of the OLS estimate $\beta_{\mathrm{OLS},i,t}^{\mathrm{BEAR}}$. Then, for each month t we take the prior mean, $\beta_{\mathrm{Prior},t}^{\mathrm{BEAR}}$, to be the average $\beta_{\mathrm{OLS},j,m}^{\mathrm{BEAR}}$ across all stock j and month m observations in months m between December 1996 and month t, inclusive,

$$\beta_{\mathrm{Prior},t}^{\mathrm{BEAR}} = \frac{\sum_{m\le t}\sum_{j\in S_m}\beta_{\mathrm{OLS},j,m}^{\mathrm{BEAR}}}{n_t}, \tag{8}$$

and the prior variance, $\sigma_{\mathrm{Prior},t}^2$, to be the sample variance of $\beta_{\mathrm{OLS},j,m}^{\mathrm{BEAR}}$ over the same period,

$$\sigma_{\mathrm{Prior},t}^2 = \frac{\sum_{m\le t}\sum_{j\in S_m}\left(\beta_{\mathrm{OLS},j,m}^{\mathrm{BEAR}} - \beta_{\mathrm{Prior},t}^{\mathrm{BEAR}}\right)^2}{n_t - 1}, \tag{9}$$

where S_m is the set of stocks for which values of $\beta_{\mathrm{OLS},j,m}^{\mathrm{BEAR}}$ can be calculated and n_t is the number of stock-month observations with valid values of $\beta_{\mathrm{OLS},j,m}^{\mathrm{BEAR}}$ over all months m between December 1996 and month t, inclusive. Finally, the Bayes-adjusted estimate that we use as our focal variable throughout the paper, $\beta_{i,t}^{\mathrm{BEAR}}$, is the inverse variance–weighted average of the OLS estimate and the prior mean, computed based on information available at time t.

$$\beta_{i,t}^{\mathrm{BEAR}} = \frac{\left(\sigma_{\mathrm{OLS},i,t}^2\right)^{-1}}{\left(\sigma_{\mathrm{OLS},i,t}^2\right)^{-1} + \left(\sigma_{\mathrm{Prior},t}^2\right)^{-1}}\beta_{\mathrm{OLS},i,t}^{\mathrm{BEAR}} + \frac{\left(\sigma_{\mathrm{Prior},t}^2\right)^{-1}}{\left(\sigma_{\mathrm{OLS},i,t}^2\right)^{-1} + \left(\sigma_{\mathrm{Prior},t}^2\right)^{-1}}\beta_{\mathrm{Prior},t}^{\mathrm{BEAR}}. \tag{10}$$

Intuitively, $\beta_{i,t}^{\mathrm{BEAR}}$ gives more (less) weight to the OLS estimate when the precision of the OLS estimate is high (low). The theoretical derivation of the Bayes adjustment is in Section 2 of the Online Appendix.[18]

Bear betas computed from regression Eq. (7) measure the stock's exposure to the component of the AD Bear return that is orthogonal to the market return. This orthogonal component is identical to the return of the AD Bear portfolio hedged with respect to market risk (i.e., the residual from regressing AD Bear returns on market returns). In Section 2, we illustrate theoretically that the hedged AD Bear portfolio is highly responsive to bear market risk. Therefore, we expect large hedged AD Bear portfolio returns to coincide with economic events affecting investors' forward-looking assessment of future bear market states.[19] In Fig. 2, we plot the time series of residuals from the full-sample CAPM regression and indicate the five largest residuals with the numbers 1–5. The largest residual of 30.3% occurs during the five–trading day period between the end of February 26, 2007 and the end of March 5, 2007. During this period, the Chinese stock market crashed. The SSE Composite Index of the Shanghai Stock Exchange experienced a 9% drop on Feb 27, 2007, the largest in ten years. The second largest residual of 16.8% comes between April 29, 2010 and May 6, 2010. This period coincides with the Flash Crash on May 6, 2010, when major stock indices collapsed and rebounded very rapidly. The third largest residual occurs between May 31, 2011 and June 7, 2011, a period characterized by a series of bad economic news. Moody's cut Greece's credit rating by three notches to an extremely speculative level. Both the ISM manufacturing report and the private sector employment report came in well below economists' expectations. The fourth largest residual (August 18, 2015 through August 25, 2015) corresponds to the Chinese stock market's Black Monday when the Shanghai Composite Index tumbled 8.5%, the biggest loss since February 2007. Finally, the fifth largest residual occurs between December 29, 2014 and January 6, 2015, when the price of oil fell below \$50 a barrel for the first time in nearly six years and Greece's snap election renewed political turmoil. Notably, market returns during these five periods are only moderately negative. Therefore, the largest hedged AD Bear returns appear to be associated with im-

[18] In Section 6, we present the results of tests using bear beta that is not adjusted using the shrinkage methodology. The results remain very strong among large and liquid stocks. When examining all stocks, the results are slightly weaker, consistent with the unadjusted value being a noisier measure of a stock's true bear beta for illiquid and small stocks and the adjustment successfully reducing measurement error.

[19] Economic events that induce large negative market returns would not be captured by the hedged AD Bear return, which has been orthogonalized to the market return.

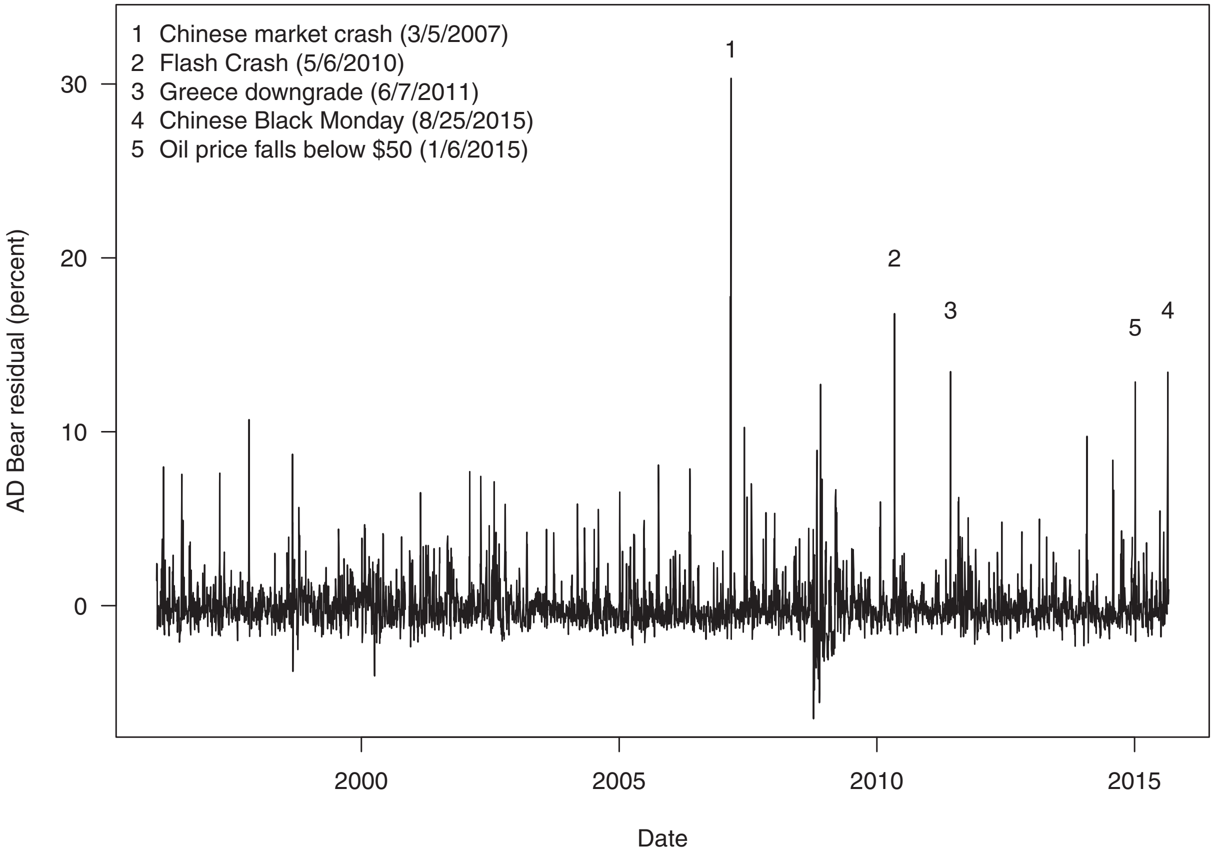

Fig. 2. AD Bear residuals from the capital asset pricing model. The figure shows the residuals from a regression of AD Bear excess returns on market excess returns (MKT). The numbers 1–5 indicate the five largest residuals, in decreasing order.

portant negative economic events, but these events are different from events that drive the largest negative market returns. This is consistent with the notion that bear market risk can increase even in the absence of a realized bear market state.

4.2. Samples

We use three different samples, which we term All Stocks, Liquid, and Large Cap, in our examination of the relation between bear beta and expected stock returns. Each month t, the All Stocks sample consists of all US-based common stocks in the Center for Research in Security Prices database that have a valid month t value of β^{BEAR}. The Liquid sample is the subset of the All Stocks sample with Amihud (2002) illiquidity (ILLIQ) values that are less than or equal to the 80th percentile month t ILLIQ value among NYSE stocks.[20] Finally, the Large Cap sample is the subset of the All Stocks sample with market capitalization (MKTCAP) values that are greater than or equal to the 50th percentile value of MKTCAP among NYSE stocks.[21] Because mispricing is likely to be small among liquid and large cap stocks, we use the Liquid and Large Cap samples to distinguish between risk pricing and mispricing explanations for our results. Our samples cover the months t (one-month-ahead return months $t+1$) from December 1996 (January 1997) through August 2015 (September 2015). This period is chosen because December 1996 and August 2015 are the first and last months for which β^{BEAR} can be estimated using a full year's worth of AD Bear returns due to the availability of the OM data.

Table 4 presents the time series averages of monthly cross-sectional summary statistics for β^{BEAR}, MKTCAP, and ILLIQ. In the average month, All Stocks sample values of β^{BEAR} range from -1.71 to 2.13, with mean (0.07) and median (0.05) values that are very close to zero and a standard deviation of 0.41. The distribution of β^{BEAR} has a small positive skewness of 0.25. The mean (median) MKTCAP of stocks in the All Stocks sample is \$3.2 billion (\$308 million), and the mean (median) value of ILLIQ is 197 (4.75). The All Stocks sample has, on average, 4,791 stocks per month. The distributions of β^{BEAR} in the Liquid and Large Cap samples are similar to that of the All Stocks sample. As expected, the Liquid sample has larger

[20] ILLIQ is calculated following Amihud (2002) as the absolute daily return measured in percent divided by the daily dollar trading volume in millions of dollars, averaged over all days in months $t-11$ through t, inclusive.

[21] MKTCAP is the number of shares outstanding times the stock price, recorded at the end of month t in millions of dollars.

Table 4
Summary statistics.
The table presents cross-sectional summary statistics for bear beta (β^{BEAR}), market capitalization (MKTCAP), and Amihud (2002) illiquidity (ILLIQ). The All Stocks sample includes all US-based stocks in the Center for Research in Security Prices database with a valid value of β^{BEAR}. The Liquid sample is the subset of the All Stocks sample with values of ILLIQ lower than the 80th percentile value of ILLIQ among NYSE stocks. The Large Cap sample is the subset of the All Stocks sample with MKTCAP greater than the 50th percentile MKTCAP value among NYSE stocks. This table shows the time series averages of the monthly cross-sectional mean, standard deviation, skewness, minimum value, 25th percentile value, median value, 75th percentile value, maximum value, and number of observations with valid values for β^{BEAR}, MKTCAP, and ILLIQ using each sample. The summary statistics cover the 225 months t from December 1996 through August 2015. Panels A, B, and C present results for the All Stocks, Liquid, and Large Cap samples, respectively.

Variable	Mean	Standard deviation	Skewness	Minimum	25th percentile	Median	75th percentile	Maximum	N
Panel A: All Stocks sample									
β^{BEAR}	0.07	0.41	0.25	−1.71	−0.19	0.05	0.31	2.13	4791
MKTCAP	3174	15158.20	13.67	1	75	308	1334	406290	4788
ILLIQ	197.47	1081.90	17.41	0.00	0.45	4.75	48.68	36793.83	4505
Panel B: Liquid sample									
β^{BEAR}	0.08	0.38	0.27	−1.42	−0.16	0.06	0.31	1.74	2042
MKTCAP	6993	22299.12	9.13	69	743	1600	4366	406290	2042
ILLIQ	0.69	0.78	1.26	0.00	0.09	0.34	1.06	3.01	2042
Panel C: Large Cap sample									
β^{BEAR}	0.05	0.34	0.32	−1.18	−0.17	0.02	0.24	1.51	1006
MKTCAP	13154	30299.99	6.61	1598	2472	4315	10653	406290	1006
ILLIQ	0.26	1.52	18.77	0.00	0.03	0.08	0.20	42.56	1006

and more liquid stocks than the All Stocks sample, and Large Cap sample stocks are larger and more liquid than Liquid sample stocks. The Liquid (Large Cap) sample has 2,042 (1,006) stocks in the average month.

4.3. β^{BEAR}-sorted portfolios

In this subsection, we examine the β^{BEAR}-sorted portfolios' post-formation returns and bear market risk exposures.

4.3.1. Post-formation portfolio returns

We begin our examination of the relation between bear beta and expected stock returns with a univariate portfolio analysis using β^{BEAR} as the sort variable. At the end of each month t, all stocks in the given sample are sorted into decile portfolios based on an ascending ordering of β^{BEAR}. We then calculate the value-weighted average month $t+1$ excess return for each of the decile portfolios, as well as for the zero-investment portfolio that is long the β^{BEAR} decile ten portfolio and short the β^{BEAR} decile one portfolio (β^{BEAR} $10-1$ portfolio).[22]

Panel A of Table 5 shows that, for the All Stocks sample, average excess returns are nearly monotonically decreasing across β^{BEAR} deciles. The β^{BEAR} decile one portfolio generates an average excess return of 0.98% per month and the average excess return of the decile ten portfolio is −0.15% per month. The β^{BEAR} $10-1$ portfolio average return of −1.13% per month is economically large and highly statistically significant with a NW t-statistic of −2.70.

To examine whether the pattern in the excess returns of the β^{BEAR}-sorted portfolios is a manifestation of exposure to previously identified risk factors, we calculate the abnormal returns of the decile portfolios relative to the CAPM, FF3, FFC, Q, and FF5 factor models. The results demonstrate that standard risk factors do not explain the relation between β^{BEAR} and average returns because the alphas exhibit a similar monotonically decreasing pattern across β^{BEAR} deciles and the alpha of the β^{BEAR} $10-1$ portfolio relative to each of the factor models is negative and statistically significant. The β^{BEAR} $10-1$ portfolio generates monthly alpha of −1.48% per month (t-statistic = −3.81), −1.34% (t-statistic = −4.56), −1.25% (t-statistic = −3.80), −0.82% (t-statistic = −2.72), and −0.71% (t-statistic = −2.45) relative to the CAPM, FF3, FFC, Q, and FF5 factor models, respectively.

4.3.2. Post-formation sensitivities to AD Bear

Theoretically, a factor model indicates contemporaneous relations between the true factor loading and expected returns. The empirical tests in Section 4.3.1 use the average post-formation returns as the measure of expected returns for portfolios sorted on the pre-formation β^{BEAR} and implicitly assume that these portfolios have differential post-formation exposure to bear market risk. To test whether this is the case, we calculate the post-formation sensitivities of the decile portfolio returns to the AD Bear return by regressing the entire time series of post-formation five-day overlapping excess returns of the β^{BEAR} decile portfolios on the contemporaneous AD Bear excess returns and MKT, as in Eq. (7). The portfolios are still rebalanced at the end of each month t.

As emphasized in Ang et al. (2006b, page 271), "finding large spreads in the post-formation loadings is a very

[22] The excess stock return in month $t+1$ is defined as the delisting-adjusted (Shumway, 1997) stock return minus the return of the one-month US Treasury bill in month $t+1$, recorded in percent. If the stock is delisted in month $t+1$, if a delisting return is provided by CRSP, we take the month $t+1$ return of the stock to be the delisting return. If no delisting return is available, then we determine the stock's return based on the delisting code in CRSP. If the delisting code is 500 (reason unavailable), 520 (went to over the counter), 551–573 or 580 (various reasons), 574 (bankruptcy), or 584 (does not meet exchange financial guidelines), we take the stock's return during the delisting month to be −30%. If the delisting code has a value other than the previously mentioned values and there is no delisting return, we take the stock's return during the delisting month to be −100%.

Table 5
β^{BEAR}-sorted portfolios returns.
The table presents the results of univariate portfolio analyses of the relation between β^{BEAR} and future stock returns. Each month t, all stocks in the sample are sorted into decile portfolios based on an ascending sort of β^{BEAR}. The columns labeled "β^{BEAR} 1" through "β^{BEAR} 10" present results for the first through tenth β^{BEAR} decile portfolios. The column labeled "β^{BEAR} 10−1" presents results for a portfolio that is long stocks in the β^{BEAR} decile ten portfolio and short stocks in the β^{BEAR} decile one portfolio. The table shows the average month $t+1$ value-weighted excess return (Excess return), alphas (α) relative to the capital asset pricing model (CAPM), Fama and French (1993) three-factor model (FF3), Fama and French (1993) and Carhart (1997) four-factor model (FFC), Hou et al. (2015) Q-factor model (Q), and Fama and French (2015) five-factor model (FF5), and factor sensitivities relative to the FF5 factors. Newey and West (1987)–adjusted t-statistics using 12 lags are presented in parentheses. The row labeled "Pre-formation" shows the time series average of the monthly value-weighted average values of pre-formation β^{BEAR} for each of the portfolios. The row labeled "Post-formation" presents the corresponding post-formation β^{BEAR}, calculated as the slope coefficient on AD Bear portfolio excess returns from a regression of the daily five-day overlapping portfolio excess returns on the contemporaneous market (MKT) and AD Bear portfolio excess returns. t-statistics reported in parentheses for the post-formation sensitivities are adjusted following Newey and West (1987) using 22 lags. Panels A, B, and C present results for the All Stocks, Liquid, and Large Cap samples, respectively.

Value	β^{BEAR} 1	β^{BEAR} 2	β^{BEAR} 3	β^{BEAR} 4	β^{BEAR} 5	β^{BEAR} 6	β^{BEAR} 7	β^{BEAR} 8	β^{BEAR} 9	β^{BEAR} 10	β^{BEAR} 10 − 1
Panel A: All Stocks sample											
Excess Return	0.98	0.82	0.66	0.47	0.62	0.41	0.48	0.39	0.32	−0.15	−1.13
	(2.62)	(2.75)	(2.29)	(1.58)	(1.74)	(1.02)	(1.14)	(0.78)	(0.59)	(−0.24)	(−2.70)
CAPM α	0.47	0.36	0.22	0.01	0.10	−0.13	−0.09	−0.24	−0.42	−1.02	−1.48
	(2.44)	(2.14)	(1.58)	(0.08)	(1.21)	(−0.84)	(−0.81)	(−1.25)	(−2.11)	(−3.77)	(−3.81)
FF3 α	0.39	0.31	0.20	−0.01	0.12	−0.08	−0.04	−0.23	−0.39	−0.95	−1.34
	(2.46)	(2.33)	(1.82)	(−0.07)	(1.38)	(−0.61)	(−0.41)	(−1.33)	(−2.54)	(−4.79)	(−4.56)
FFC α	0.42	0.34	0.21	0.02	0.12	−0.09	−0.03	−0.17	−0.34	−0.83	−1.25
	(2.39)	(2.64)	(1.79)	(0.14)	(1.15)	(−0.67)	(−0.34)	(−0.99)	(−1.96)	(−3.92)	(−3.80)
Q α	0.31	0.24	0.17	0.06	0.15	0.04	0.01	−0.07	−0.18	−0.51	−0.82
	(1.76)	(1.88)	(1.37)	(0.37)	(1.10)	(0.32)	(0.06)	(−0.44)	(−1.12)	(−2.46)	(−2.72)
FF5 α	0.24	0.21	0.06	−0.02	0.12	−0.01	0.05	−0.04	−0.12	−0.47	−0.71
	(1.34)	(1.66)	(0.77)	(−0.19)	(1.22)	(−0.07)	(0.48)	(−0.30)	(−1.00)	(−2.31)	(−2.45)
β_{MKT}	1.10	1.01	0.94	0.91	0.99	0.97	1.02	1.07	1.20	1.25	0.15
	(20.77)	(18.05)	(34.09)	(17.29)	(31.20)	(25.73)	(29.97)	(21.81)	(18.99)	(16.20)	(1.37)
β_{SMB_5}	0.02	−0.16	−0.05	0.01	−0.04	0.04	−0.00	0.13	0.24	0.40	0.37
	(0.28)	(−2.28)	(−0.95)	(0.12)	(−1.01)	(0.83)	(−0.02)	(2.43)	(3.25)	(3.92)	(2.68)
β_{HML}	0.10	0.08	−0.04	0.05	−0.04	−0.12	−0.14	0.04	0.05	−0.10	−0.20
	(0.82)	(0.81)	(−0.81)	(0.45)	(−0.67)	(−2.33)	(−1.99)	(0.43)	(0.47)	(−0.61)	(−0.81)
β_{RMW}	0.11	0.04	0.17	0.04	−0.01	−0.06	−0.15	−0.24	−0.31	−0.76	−0.87
	(0.59)	(0.26)	(1.65)	(0.60)	(−0.24)	(−0.82)	(−2.21)	(−1.85)	(−2.41)	(−5.73)	(−2.94)
β_{CMA}	0.39	0.36	0.26	−0.00	0.01	−0.17	−0.10	−0.31	−0.59	−0.62	−1.01
	(1.60)	(1.69)	(3.17)	(−0.02)	(0.06)	(−1.00)	(−0.82)	(−1.91)	(−4.56)	(−2.49)	(−2.40)
Pre-formation β^{BEAR}	−0.58	−0.32	−0.19	−0.08	0.01	0.09	0.19	0.31	0.47	0.80	1.38
Post-formation β^{BEAR}	−0.05	−0.03	−0.03	−0.03	−0.01	−0.00	0.03	0.11	0.16	0.18	0.23
	(−1.70)	(−0.94)	(−1.39)	(−1.75)	(−0.54)	(−0.23)	(1.33)	(2.99)	(3.71)	(3.27)	(3.11)
Panel B: Liquid sample											
Excess Returns	0.90	0.79	0.69	0.67	0.56	0.35	0.46	0.37	0.35	−0.18	−1.08
	(2.60)	(2.67)	(2.39)	(2.24)	(1.54)	(0.82)	(1.14)	(0.73)	(0.71)	(−0.27)	(−2.35)
CAPM α	0.42	0.35	0.25	0.23	0.05	−0.22	−0.11	−0.27	−0.38	−1.07	−1.49
	(2.50)	(2.08)	(1.65)	(1.46)	(0.56)	(−1.36)	(−0.77)	(−1.45)	(−1.84)	(−3.49)	(−3.52)
FF3 α	0.35	0.32	0.23	0.20	0.06	−0.15	−0.05	−0.23	−0.35	−0.98	−1.33
	(2.82)	(2.28)	(1.74)	(1.58)	(0.67)	(−1.26)	(−0.50)	(−1.54)	(−2.45)	(−4.71)	(−5.01)
FFC α	0.38	0.35	0.21	0.19	0.08	−0.11	−0.04	−0.16	−0.26	−0.84	−1.23
	(2.81)	(2.45)	(1.55)	(1.45)	(0.76)	(−0.82)	(−0.35)	(−1.06)	(−1.64)	(−3.66)	(−4.06)
Q α	0.30	0.25	0.13	0.12	0.08	−0.04	0.02	−0.08	−0.09	−0.55	−0.85
	(2.08)	(1.62)	(1.07)	(0.87)	(0.61)	(−0.37)	(0.25)	(−0.48)	(−0.60)	(−2.42)	(−3.07)
FF5 α	0.22	0.21	0.06	0.10	0.06	−0.11	0.07	−0.03	−0.06	−0.49	−0.71
	(1.37)	(1.52)	(0.59)	(0.90)	(0.59)	(−0.93)	(0.75)	(−0.20)	(−0.51)	(−2.70)	(−2.81)
β_{MKT}	1.04	0.97	0.99	0.93	0.99	1.03	1.00	1.10	1.19	1.31	0.27
	(20.25)	(21.26)	(20.32)	(44.13)	(25.43)	(33.86)	(30.89)	(22.66)	(18.79)	(15.15)	(2.43)
β_{SMB_5}	−0.04	−0.19	−0.14	−0.03	−0.04	−0.01	−0.03	0.05	0.21	0.29	0.33
	(−0.49)	(−2.73)	(−2.64)	(−0.45)	(−0.97)	(−0.19)	(−0.57)	(0.72)	(2.36)	(2.59)	(2.17)
β_{HML}	0.09	0.06	−0.02	0.02	0.06	−0.14	−0.11	0.04	0.06	−0.09	−0.18
	(0.96)	(0.58)	(−0.24)	(0.42)	(0.93)	(−2.72)	(−1.75)	(0.43)	(0.55)	(−0.54)	(−0.79)
β_{RMW}	0.11	0.06	0.21	0.14	0.09	0.02	−0.15	−0.25	−0.31	−0.72	−0.83
	(0.59)	(0.50)	(2.75)	(1.92)	(1.46)	(0.43)	(−1.54)	(−1.88)	(−1.98)	(−5.23)	(−2.83)
β_{CMA}	0.35	0.34	0.30	0.17	−0.15	−0.22	−0.22	−0.38	−0.61	−0.70	−1.05
	(1.42)	(2.11)	(2.13)	(2.88)	(−1.04)	(−1.38)	(−1.71)	(−2.28)	(−4.10)	(−2.79)	(−2.48)
Pre-formation β^{BEAR}	−0.52	−0.28	−0.16	−0.07	0.02	0.11	0.20	0.31	0.46	0.77	1.29
Post-formation β^{BEAR}	−0.04	−0.04	−0.05	−0.01	−0.04	−0.00	0.02	0.10	0.16	0.18	0.22
	(−1.42)	(−1.36)	(−2.08)	(−0.78)	(−2.22)	(−0.04)	(0.73)	(2.12)	(3.80)	(3.20)	(2.91)

(*continued on next page*)

Table 5 (*continued*)

Value	β^{BEAR} 1	β^{BEAR} 2	β^{BEAR} 3	β^{BEAR} 4	β^{BEAR} 5	β^{BEAR} 6	β^{BEAR} 7	β^{BEAR} 8	β^{BEAR} 9	β^{BEAR} 10	β^{BEAR} 10 − 1
Panel C: Large Cap sample											
Excess Returns	0.83	0.80	0.64	0.57	0.67	0.60	0.35	0.27	0.25	−0.07	−0.90
	(2.46)	(2.84)	(2.24)	(1.77)	(2.21)	(1.79)	(0.81)	(0.60)	(0.47)	(−0.12)	(−2.05)
CAPM α	0.36	0.37	0.23	0.14	0.22	0.11	−0.20	−0.31	−0.43	−0.92	−1.28
	(2.34)	(2.78)	(1.25)	(0.90)	(1.60)	(1.22)	(−1.41)	(−1.71)	(−1.83)	(−2.81)	(−2.95)
FF3 α	0.31	0.36	0.20	0.12	0.21	0.11	−0.14	−0.25	−0.36	−0.81	−1.12
	(2.85)	(2.81)	(1.49)	(0.92)	(1.77)	(1.27)	(−1.07)	(−1.95)	(−2.10)	(−3.82)	(−4.41)
FFC α	0.33	0.35	0.17	0.10	0.17	0.09	−0.13	−0.23	−0.32	−0.70	−1.02
	(2.89)	(2.70)	(1.18)	(0.75)	(1.47)	(1.02)	(−0.87)	(−1.86)	(−1.74)	(−3.15)	(−3.79)
Q α	0.25	0.24	0.08	0.00	0.09	0.08	−0.11	−0.12	−0.17	−0.41	−0.66
	(2.02)	(1.86)	(0.61)	(0.04)	(0.80)	(0.96)	(−0.77)	(−0.92)	(−1.13)	(−1.89)	(−2.73)
FF5 α	0.18	0.22	0.06	−0.01	0.09	0.06	−0.09	−0.08	−0.12	−0.32	−0.50
	(1.25)	(1.81)	(0.56)	(−0.08)	(0.91)	(0.72)	(−0.64)	(−0.71)	(−0.88)	(−1.92)	(−2.30)
β_{MKT}	1.03	0.96	0.93	0.96	0.94	0.96	1.04	1.00	1.15	1.26	0.23
	(22.31)	(21.43)	(40.25)	(22.81)	(38.36)	(35.95)	(23.73)	(26.03)	(20.40)	(14.98)	(2.11)
β_{SMB_5}	−0.11	−0.19	−0.16	−0.16	−0.03	0.05	−0.10	−0.02	0.00	0.13	0.24
	(−1.38)	(−3.45)	(−4.18)	(−3.45)	(−0.60)	(1.00)	(−2.08)	(−0.33)	(0.04)	(1.12)	(1.38)
β_{HML}	0.08	0.04	0.08	0.06	−0.03	−0.03	−0.11	−0.06	0.01	−0.10	−0.18
	(0.79)	(0.47)	(0.96)	(0.83)	(−0.50)	(−0.50)	(−2.17)	(−0.73)	(0.07)	(−0.59)	(−0.77)
β_{RMW}	0.11	0.15	0.21	0.18	0.19	0.13	−0.01	−0.24	−0.29	−0.73	−0.84
	(0.63)	(1.78)	(3.54)	(2.27)	(3.19)	(2.89)	(−0.22)	(−1.94)	(−2.04)	(−4.70)	(−2.70)
β_{CMA}	0.34	0.29	0.20	0.19	0.15	−0.05	−0.17	−0.24	−0.47	−0.66	−1.00
	(1.53)	(2.49)	(2.11)	(2.09)	(2.15)	(−0.72)	(−1.27)	(−1.41)	(−3.17)	(−3.08)	(−2.64)
Pre-formation β^{BEAR}	−0.48	−0.28	−0.17	−0.09	−0.01	0.06	0.14	0.24	0.38	0.67	1.15
Post-formation β^{BEAR}	−0.03	−0.05	−0.05	−0.04	−0.03	−0.05	−0.00	0.01	0.16	0.19	0.22
	(−1.13)	(−2.22)	(−2.18)	(−1.66)	(−1.45)	(−4.00)	(−0.04)	(0.51)	(3.18)	(3.49)	(2.92)

stringent requirement" in tests of a factor risk-based explanation of a cross-sectional pattern in returns. The results in Table 5 indicate that the β^{BEAR} 10 − 1 portfolio has a strong positive post-formation AD Bear sensitivity of 0.23 (t-statistic = 3.11). For sake of comparison, Table 5 presents the value-weighted average value of (pre-formation) β^{BEAR} for each of the decile portfolios. By construction, the value-weighted pre-formation values of β^{BEAR} increase from −0.58 for the β^{BEAR} decile one portfolio to 0.80 for β^{BEAR} decile ten portfolio. While pre-formation β^{BEAR} is an imperfect measure of the true forward-looking factor loading, it is sufficiently accurate to generate economically and statistically significant post-formation exposure to AD Bear returns. The significant dispersion in post-formation bear market risk exposure is noteworthy when compared with the lack of post-formation dispersion exhibited by other non-stock return-based sensitivity measures. For example, Table 1 in Ang et al. (2006b) shows that, for quintile portfolios formed by sorting on VIX beta, the average difference in pre-formation VIX betas between the fifth and first quintile is 4.27. However, the average difference in post-formation VIX betas is only 0.051, a reduction of almost 99%. Cremers et al. (2015) also find that their pre-formation jump betas are poor predictors of post-formation jump betas.

While this regression indicates that the β^{BEAR} 10 − 1 portfolio has significant post-formation exposure to bear market risk, the intercept coefficient (not reported) remains negative and significant. This raises the interesting question of whether bear market risk is priced differently in the stock and option markets. Several empirical issues make us hesitant to draw strong conclusions about this question from the intercept of this regression. First, as discussed in Section 3.4, costs associated with trading the AD Bear portfolio can substantially affect the obtainable monthly premium associated with AD Bear returns. Second, AD Bear excess returns are based on the average of the bid and the offer prices for options and thus perhaps do not perfectly measure innovations in bear market risk due to microstructure issues such as bid-ask bounce and nonsynchronous trading. The resulting errors-in-variables problem would bias the estimated bear market risk exposure of the β^{BEAR} 10 − 1 portfolio toward zero. Finally, to fully explain the premium earned by the β^{BEAR} 10 − 1 portfolio using an empirical factor model we would need to know the true set of factors and have precise estimates of potentially time-varying risk premia and factor loadings for all factors [see Ang et al. (2006b) for similar discussions]. For these reasons, a complete answer to this question requires a fuller investigation, which we leave to future research.

4.3.3. Subsample analysis

If the negative cross-sectional relation between β^{BEAR} and future stock returns is truly indicative of a risk pricing effect, we expect the effect to remain strong in liquid and large stocks. If the negative relation between β^{BEAR} and future stock returns captures mispricing, we would expect the relation to be weak or nonexistent among liquid and large stocks for which limits to arbitrage (Shleifer and Vishny, 1997) are unlikely to bind. To distinguish between the risk pricing and mispricing explanations, we repeat the portfolio tests using the Liquid and Large Cap samples.

Results for the Liquid sample, shown in Panel B of Table 5, are very similar to those of the All Stocks sample. The Liquid sample average portfolio excess returns decrease strongly across β^{BEAR} deciles. The β^{BEAR} 10 − 1 portfolio generates an economically large and highly statistically significant average return of −1.08% per month (t-statistic = −2.35), with alphas ranging from −1.49% per month (t-statistic = −3.52) using the CAPM to −0.71% per month (t-statistic = −2.81) using the FF5 model. The Liquid sample β^{BEAR} 10 − 1 portfolio has a post-formation sensitivity of 0.22 (t-statistic = 2.91) to AD Bear excess returns, indicating that the portfolio sort is effective at generating assets with strong variation in post-formation exposure to bear market risk.

The Large Cap sample results in Panel C of Table 5 are once again similar to those of the other two samples. The portfolio excess returns and alphas exhibit a strong decreasing pattern across β^{BEAR} deciles. The β^{BEAR} 10 − 1 portfolio generates an economically large and highly statistically significant negative alpha relative to all factor models, ranging from −1.28% per month (t-statistic = −2.95) using the CAPM to −0.50% per month (t-statistic = −2.30) using the FF5 model. In all three samples, the alphas from models that include profitability and investment factors, namely, the Q and FF5 models, are substantially lower than the alphas relative to other factor models, and sensitivities of the β^{BEAR} 10 − 1 portfolio to the RMW and CMA factors in the FF5 model are economically large and highly significant. These results suggest that the premium earned by the profitability and investment factors could be related to bear market risk. Once again, supportive of a risk-based explanation for the pattern in returns, the β^{BEAR} 10 − 1 portfolio exhibits a strong positive post-formation sensitivity to AD Bear excess returns.

The β^{BEAR} 10 − 1 portfolio has a positive estimated exposure to MKT in all three samples. Stocks with high market betas generate lower risk-adjusted returns than stocks with low market betas (Frazzini and Pedersen, 2014), a phenomenon known as the betting-against-beta (BAB) effect. To test whether the betting-against-beta phenomenon explains our results, we augment each of our risk models with the Frazzini and Pedersen (2014) BAB factor and repeat our factor analyses using the augmented models. The results of these analyses, presented in Table OA1 of the Online Appendix, show that the alpha of the β^{BEAR} 10 − 1 portfolio remains negative, economically large, and statistically significant when the BAB factor is included in the factor models.

5. Bear beta and related risk measures

Having demonstrated a strong negative cross-sectional relation between bear beta and expected stock returns that is not explained by standard risk factors, we proceed to investigate the possibility that this relation can be explained by risk variables that are plausibly related to bear market risk. Average values of the risk variables for stocks in each β^{BEAR} decile portfolio are shown in Table 6. We describe each risk variable as we discuss the corresponding results. More detailed descriptions of the control variables are provided in Section 3 of the Online Appendix.

5.1. Bivariate portfolio analyses

We use the risk variables as controls and test the robustness of our univariate β^{BEAR} portfolio results by constructing bivariate portfolios that are neutral to a control variable while having variation in β^{BEAR}. At the end of each month t, we first sort all stocks into deciles based on ascending values of the control variable. Within each control variable decile, we then sort stocks into decile portfolios based on an ascending ordering of β^{BEAR}. We then calculate the value-weighted month $t+1$ excess return for each of the resulting portfolios. Next, we compute the average month $t+1$ excess return across the control variable decile portfolios within each β^{BEAR} decile and refer to this as the bivariate β^{BEAR} decile portfolio excess return. Finally, we calculate the difference in month $t+1$ returns between the bivariate β^{BEAR} decile ten and decile one portfolios (β^{BEAR} 10 − 1 portfolio). Because the bivariate β^{BEAR} decile portfolios have similar values of the control variable, any return pattern across the bivariate β^{BEAR} decile portfolios is unlikely to be driven by the control variable. The results of the bivariate portfolio analyses are shown in Table 7.

We first control for CAPM beta (β^{CAPM}), measured as the slope coefficient from a one-year rolling window regression of daily excess stock returns on MKT. Table 6 shows that, consistent with the positive market factor exposure of the univariate-sort β^{BEAR} 10 − 1 (see Table 5), in all three samples, stocks that have high β^{BEAR} tend to also have high β^{CAPM}. While most asset pricing models predict that CAPM beta should be positively priced, suggesting that CAPM beta should not explain the negative relation between bear beta and average stock returns, this analysis serves as an additional test of whether the betting-against-beta effect can explain our results. Table 7 shows that in the All Stocks sample the bivariate β^{BEAR} 10 − 1 portfolio that is neutral to β^{CAPM} earns a highly significant CAPM alpha of −0.78% per month (t-statistic = −4.00). Furthermore, when we benchmark against the FF3, FFC, Q, and FF5 models, this portfolio's alphas range from −0.53% to −0.77% per month with t-statistics between −2.19 and −3.00. Results using the Liquid and Large Cap samples are similar. Therefore, controlling for CAPM beta does not appear to explain the negative relation between bear beta and expected returns.

We then investigate whether downside beta studied in Ang et al. (2006a) can explain the negative relation between bear beta and expected stock returns. Ang et al. (2006a) find a positive relation between average stock returns and downside beta (β^-), measured as the slope coefficient from a one-year rolling window regression of daily excess stock returns on MKT using only below-average MKT days. While both β^- and β^{BEAR} are measures of downside risk, they capture economically different sources of risk. β^- measures the covariance between the stock return and the market return when a bear state occurs, and β^{BEAR} measures the covariance between the stock return and the innovation in the probability of future bear states. Because β^- is strongly correlated with CAPM market beta, to control for market risk, Ang et al. (2006a) compute relative downside beta, $\beta^- - \beta^{CAPM}$, and show that this measure is also positively related to expected stock returns.[23] β^{BEAR} is more comparable to $\beta^- - \beta^{CAPM}$ than β^-

[23] In unreported results, we confirm the Ang et al. (2006a) finding that the correlation between β^- and β^{CAPM} is above 0.7.

Table 6

β^{BEAR}-sorted portfolios: average risk characteristics.

The table presents average values of risk variables for stocks in each of the univariate decile portfolios formed by sorting on β^{BEAR}. Each month t, all stocks in the sample are sorted into decile portfolios based on an ascending sort of β^{BEAR}. The columns labeled "β^{BEAR} 1" through "β^{BEAR} 10" present results for the β^{BEAR} decile one through ten portfolios. The table shows the time series average of the monthly equal-weighted month t values for each risk variable in each portfolio. Results for β^{JUMP} and β^{VOL} cover the 184 months t from December 1996 through March 2012. Results for $\beta^{\Delta SKEW}$ cover the 133 months t from December 1996 through December 2007. Results for β^{TAIL} cover the 181 months t from December 1996 through December 2011. All other results cover the 225 months t from December 1996 through August 2015. Panels A, B, and C present results for the All Stocks, Liquid, and Large Cap samples, respectively.

Variable	β^{BEAR} 1	β^{BEAR} 2	β^{BEAR} 3	β^{BEAR} 4	β^{BEAR} 5	β^{BEAR} 6	β^{BEAR} 7	β^{BEAR} 8	β^{BEAR} 9	β^{BEAR} 10
Panel A: All Stocks sample										
β^{CAPM}	0.77	0.76	0.75	0.75	0.77	0.81	0.86	0.93	1.01	1.14
β^{-}	0.96	0.87	0.84	0.82	0.83	0.86	0.90	0.96	1.03	1.13
$\beta^{-}-\beta^{CAPM}$	0.19	0.12	0.09	0.07	0.06	0.05	0.04	0.03	0.02	−0.01
$\beta^{\Delta VIX}$	−0.04	−0.01	−0.01	0.01	0.01	0.02	0.03	0.05	0.07	0.11
β^{VOL}	−0.05	−0.02	−0.01	−0.00	0.00	0.02	0.02	0.03	0.04	0.08
β^{JUMP}	−0.05	−0.03	−0.02	−0.01	−0.01	−0.00	−0.00	0.00	0.01	0.03
COSKEW	−1.89	−1.39	−1.17	−1.02	−0.82	−0.76	−0.69	−0.63	−0.46	−0.12
$\beta^{\Delta SKEW}$	0.40	0.26	0.21	0.08	0.05	0.11	0.20	0.04	0.01	−0.13
β^{TAIL}	21.70	18.43	17.65	16.38	16.27	15.98	16.61	16.82	16.08	15.78
IVOL	3.76	3.17	2.91	2.80	2.77	2.84	2.97	3.14	3.40	4.00
Panel B: Liquid sample										
β^{CAPM}	1.08	1.00	0.98	0.97	0.99	1.03	1.08	1.16	1.26	1.45
β^{-}	1.18	1.05	1.02	1.00	1.01	1.04	1.08	1.16	1.25	1.40
$\beta^{-}-\beta^{CAPM}$	0.10	0.06	0.04	0.03	0.02	0.01	0.01	0.00	−0.01	−0.05
$\beta^{\Delta VIX}$	−0.02	−0.00	−0.00	0.00	0.01	0.02	0.03	0.05	0.08	0.13
β^{VOL}	−0.03	−0.01	−0.01	0.00	0.01	0.01	0.02	0.03	0.04	0.07
β^{JUMP}	−0.03	−0.02	−0.01	−0.01	−0.00	−0.00	0.00	0.01	0.01	0.03
COSKEW	−0.67	−0.30	−0.28	−0.27	−0.09	−0.08	0.04	0.15	0.36	0.91
$\beta^{\Delta SKEW}$	0.36	0.29	0.26	0.20	0.14	0.20	0.20	0.05	−0.02	−0.12
β^{TAIL}	10.20	9.46	8.18	9.33	8.29	9.22	9.26	9.46	8.65	6.53
IVOL	2.39	2.02	1.93	1.88	1.92	2.00	2.11	2.29	2.53	3.01
Panel C: Large Cap sample										
β^{CAPM}	1.02	0.93	0.91	0.91	0.93	0.95	0.99	1.06	1.18	1.39
β^{-}	1.11	0.98	0.95	0.94	0.95	0.96	1.00	1.06	1.16	1.35
$\beta^{-}-\beta^{CAPM}$	0.09	0.04	0.03	0.03	0.02	0.01	0.00	−0.00	−0.01	−0.04
$\beta^{\Delta VIX}$	−0.03	−0.02	−0.01	−0.01	0.00	0.00	0.01	0.04	0.06	0.11
β^{VOL}	−0.03	−0.01	−0.01	−0.00	0.00	0.01	0.01	0.02	0.03	0.06
β^{JUMP}	−0.02	−0.01	−0.01	−0.00	−0.00	0.00	0.00	0.01	0.01	0.03
COSKEW	−0.23	−0.03	−0.06	−0.04	0.01	0.24	0.35	0.46	0.63	1.32
$\beta^{\Delta SKEW}$	0.23	0.17	0.16	0.13	0.17	0.12	0.18	0.09	−0.06	−0.19
β^{TAIL}	3.54	3.19	3.64	3.64	3.86	4.40	3.89	3.34	2.04	−2.56
IVOL	1.96	1.66	1.59	1.56	1.59	1.62	1.71	1.83	2.05	2.48

because, by including the market factor in the time series regression used to compute β^{BEAR}, we effectively control for exposure to market risk. Consistent with this intuition, Table 6 indicates that the cross-sectional relation between β^{BEAR} and β^{-} is similar to that between β^{BEAR} and β^{CAPM}, likely due to the strong correlation between β^{-} and β^{CAPM}. Once we control for market risk by subtracting CAPM beta from downside beta, we find a negative cross-sectional relation between β^{BEAR} and $\beta^{-}-\beta^{CAPM}$, suggesting an overlap between stocks that lose value when bear market risk increases and stocks that co-move more with the market when the market is down. Therefore, low β^{BEAR} stocks have higher average returns perhaps because they have, on average, higher $\beta^{-}-\beta^{CAPM}$. However, Table 7 shows that controlling for either β^{-} or $\beta^{-}-\beta^{CAPM}$ does not explain the negative relation between β^{BEAR} and future stock returns. Controlling for β^{-} yields β^{BEAR} $10-1$ return spreads between −0.75% and −0.48% per month across the three samples, all of which are statistically significant at the 5% level. Controlling for $\beta^{-}-\beta^{CAPM}$ yields even more negative β^{BEAR} $10-1$ monthly return spreads of −0.94% (t-statistic = −2.32), −0.94% (t-statistic = −2.35), and −0.79% (t-statistic = −1.86) in the All Stocks, Liquid, and Large Cap samples, respectively. In all cases, the alphas relative to each of the factor models remain negative, economically large, and statistically significant. In untabulated results, we find similar results when we compute downside beta using the bottom 25%, 10%, or 5% of market return observations.

Our next tests examine whether systematic volatility or jump risk can explain the negative relation between bear beta and expected stock returns. Ang et al. (2006b) find that expected stock returns are negatively related to VIX beta ($\beta^{\Delta VIX}$), measured as the slope coefficient on the change in the VIX from a one-month rolling window regression of daily excess stock returns on MKT and VIX changes.[24] AD Bear portfolio excess returns have a large

[24] Ang et al. (2006b) use VXO (CBOE S&P 100 volatility index) instead of VIX as the measure of systematic volatility. In unreported results, we verify that our results are robust when using VXO instead of VIX.

positive correlation of 0.73 with VIX changes. However, the correlation between the component of the AD Bear portfolio excess return that is orthogonal to MKT and the component of VIX changes that is orthogonal to MKT is only 0.24, indicating that a large portion of the 0.73 correlation between AD Bear excess returns and VIX changes is driven by joint commonality with MKT. We find that the correlation between five-day VIX changes and MKT is −0.79 in our sample. This is highly consistent with the correlation of −0.79 calculated from daily returns reported in Table 1 in Chang et al. (2013). Consistent with the moderate positive correlation between the orthogonalized components of VIX changes and AD Bear excess returns, Table 6 shows that values of $\beta^{\Delta VIX}$ tend to increase across β^{BEAR} deciles, indicating a positive cross-sectional correlation between β^{BEAR} and $\beta^{\Delta VIX}$. Cremers et al. (2015) argue that changes in VIX capture a combination of changes in aggregate volatility risk (VOL) and changes in aggregate jump risk (JUMP) and design option portfolios to capture each of these risks. They find that stock-level sensitivities to both VOL (β^{VOL}) and JUMP (β^{JUMP}), each of which is measured as the sum of the coefficients on contemporaneous and lagged JUMP or VOL factor returns from a one-year rolling window regression of excess stock returns, are both negatively related

Table 7
Bivariate β^{BEAR}-sorted portfolios.

The table presents the results of bivariate portfolio analyses using a control variable and β^{BEAR} as the sort variables. The control variable is either β^{CAPM}, β^{-}, $\beta^{-} - \beta^{CAPM}$, $\beta^{\Delta VIX}$, β^{VOL}, β^{JUMP}, COSKEW, $\beta^{\Delta SKEW}$, β^{TAIL}, or IVOL. Each month t, all stocks in the sample are sorted into decile groups based on an ascending sort on the control variable. Within each control variable group, the stocks are sorted into decile portfolios based on an ascending sort on β^{BEAR}. The monthly value-weighted excess returns for each of the resulting one hundred portfolios are calculated. Within each β^{BEAR} decile, we calculate the equal-weighted average of the portfolio excess returns across the deciles of the control variable, which we refer to as the bivariate β^{BEAR} decile portfolios. The β^{BEAR} $10-1$ portfolio is a zero-investment portfolio that is long the bivariate β^{BEAR} decile ten portfolio and short the bivariate β^{BEAR} decile one portfolio. The table presents the time series averages of the month $t+1$ excess returns for the bivariate β^{BEAR} decile portfolios. For the β^{BEAR} $10-1$ portfolios, the table shows the time series averages of the month $t+1$ excess returns, alphas (α) relative to the capital asset pricing model (CAPM), Fama and French (1993) three-factor model (FF3), Fama and French (1993) and Carhart (1997) four-factor model (FFC), Hou et al. (2015) Q-factor model (Q), and Fama and French (2015) five-factor model (FF5), and factor sensitivities relative to the FF5 factors. t-statistics, adjusted following Newey and West (1987) using 12 lags, are presented in parentheses. The analyses that control for β^{JUMP} or β^{VOL} cover the 184 months t (return months $t+1$) from December 1996 (January 1997) through March 2012 (April 2012). The analyses that control for $\beta^{\Delta SKEW}$ cover the 133 months t (return months $t+1$) from December 1996 (January 1997) through December 2007 (January 2008). The analyses that control for β^{TAIL} cover the 181 months t (return months $t+1$) from December 1996 (January 1997) through December 2011 (January 2012). All other analyses cover the 225 months t (return months $t+1$) from December 1996 (January 1997) through August 2015 (September 2015). Panels A, B, and C present results for the All Stocks, Liquid, and Large Cap samples, respectively.

Portfolio	Model	Value	β^{CAPM} Avg.	β^{-} Avg.	$\beta^{-}-\beta^{CAPM}$ Avg.	$\beta^{\Delta VIX}$ Avg.	β^{VOL} Avg.	β^{JUMP} Avg.	COSKEW Avg.	$\beta^{\Delta SKEW}$ Avg.	β^{TAIL} Avg.	IVOL Avg.
Panel A: All Stocks sample												
β^{BEAR} 1		Excess return	0.82	0.84	0.89	0.95	0.93	0.87	1.10	0.93	0.95	0.89
β^{BEAR} 2		Excess return	0.65	0.75	0.84	0.87	0.73	0.82	0.80	0.67	0.83	0.76
β^{BEAR} 3		Excess return	0.58	0.63	0.67	0.61	0.73	0.57	0.79	0.67	0.45	0.51
β^{BEAR} 4		Excess return	0.63	0.47	0.69	0.64	0.53	0.60	0.67	0.54	0.45	0.44
β^{BEAR} 5		Excess return	0.70	0.67	0.52	0.49	0.43	0.44	0.63	0.55	0.58	0.62
β^{BEAR} 6		Excess return	0.49	0.57	0.49	0.65	0.75	0.49	0.77	0.69	0.65	0.61
β^{BEAR} 7		Excess return	0.66	0.74	0.73	0.52	0.56	0.49	0.51	0.60	0.39	0.61
β^{BEAR} 8		Excess return	0.44	0.41	0.47	0.47	0.23	0.45	0.46	0.16	0.32	0.55
β^{BEAR} 9		Excess return	0.53	0.52	0.47	0.44	0.36	0.19	0.51	−0.01	0.47	0.29
β^{BEAR} 10		Excess return	0.15	0.17	−0.05	−0.09	−0.25	−0.14	0.01	−0.37	0.03	−0.01
β^{BEAR} 10 − 1		Excess return	−0.67	−0.67	−0.94	−1.05	−1.18	−1.00	−1.08	−1.30	−0.92	−0.90
			(−3.24)	(−3.21)	(−2.32)	(−2.35)	(−2.49)	(−2.59)	(−2.80)	(−2.22)	(−2.86)	(−2.26)
β^{BEAR} 10 − 1	CAPM	α	−0.78	−0.82	−1.24	−1.36	−1.44	−1.24	−1.36	−1.61	−1.12	−1.14
			(−4.00)	(−4.14)	(−3.05)	(−3.10)	(−3.05)	(−3.16)	(−3.79)	(−3.06)	(−4.10)	(−3.03)
β^{BEAR} 10 − 1	FF3	α	−0.73	−0.78	−1.10	−1.23	−1.29	−1.14	−1.24	−0.95	−1.06	−1.05
			(−2.97)	(−3.81)	(−4.19)	(−4.01)	(−4.69)	(−4.24)	(−4.61)	(−2.27)	(−4.51)	(−3.60)
β^{BEAR} 10 − 1	FFC	α	−0.77	−0.75	−1.02	−1.19	−1.24	−1.13	−1.18	−1.04	−0.99	−0.99
			(−3.00)	(−3.19)	(−3.46)	(−3.47)	(−4.29)	(−3.89)	(−3.80)	(−2.25)	(−3.69)	(−3.01)
β^{BEAR} 10 − 1	Q	α	−0.53	−0.54	−0.69	−0.78	−0.85	−0.69	−0.84	−0.85	−0.69	−0.73
			(−2.19)	(−2.45)	(−2.77)	(−2.40)	(−3.10)	(−2.44)	(−2.90)	(−1.64)	(−2.59)	(−2.54)
β^{BEAR} 10 − 1	FF5	α	−0.54	−0.57	−0.64	−0.69	−0.73	−0.57	−0.81	−0.58	−0.58	−0.67
			(−2.34)	(−2.58)	(−2.78)	(−2.82)	(−3.07)	(−1.88)	(−3.13)	(−1.54)	(−2.04)	(−2.62)
β^{BEAR} 10 − 1	FF5	β_{MKT}	−0.05	0.04	0.17	0.15	0.19	0.11	0.13	−0.04	0.16	0.17
			(−0.69)	(0.61)	(2.04)	(1.43)	(1.89)	(1.06)	(1.20)	(−0.27)	(1.66)	(1.88)
β^{BEAR} 10 − 1	FF5	β_{SMB_5}	0.48	0.47	0.29	0.32	0.25	0.44	0.39	0.31	0.29	0.16
			(3.55)	(5.19)	(2.21)	(2.24)	(1.72)	(3.26)	(2.74)	(2.22)	(2.49)	(1.36)
β^{BEAR} 10 − 1	FF5	β_{HML}	−0.34	−0.21	−0.26	−0.20	−0.28	−0.24	−0.32	−0.74	0.05	−0.06
			(−1.94)	(−1.21)	(−1.10)	(−0.86)	(−1.05)	(−0.94)	(−1.24)	(−2.90)	(0.21)	(−0.29)
β^{BEAR} 10 − 1	FF5	β_{RMW}	−0.32	−0.24	−0.64	−0.74	−0.64	−0.64	−0.57	−0.49	−0.41	−0.51
			(−1.60)	(−1.37)	(−2.23)	(−2.53)	(−1.98)	(−2.12)	(−2.00)	(−1.83)	(−1.71)	(−2.12)
β^{BEAR} 10 − 1	FF5	β_{CMA}	−0.22	−0.44	−0.75	−0.86	−0.84	−0.88	−0.70	−0.74	−1.02	−0.66
			(−0.92)	(−1.64)	(−2.27)	(−2.28)	(−2.40)	(−2.35)	(−1.72)	(−1.67)	(−2.76)	(−2.21)

(continued on next page)

Table 7 (*continued*)

Portfolio	Model	Value	β^{CAPM} Avg.	β^{-} Avg.	$\beta^{-}-\beta^{CAPM}$ Avg.	$\beta^{\Delta VIX}$ Avg.	β^{VOL} Avg.	β^{JUMP} Avg.	COSKEW Avg.	$\beta^{\Delta SKEW}$ Avg.	β^{TAIL} Avg.	IVOL Avg.
Panel B: Liquid sample												
β^{BEAR} 1		Excess return	0.80	0.82	0.89	0.89	0.85	0.88	0.94	0.96	0.84	0.91
β^{BEAR} 2		Excess return	0.60	0.54	0.86	0.87	0.69	0.72	0.86	0.73	0.88	0.80
β^{BEAR} 3		Excess return	0.63	0.59	0.69	0.57	0.77	0.67	0.81	0.54	0.50	0.70
β^{BEAR} 4		Excess return	0.66	0.46	0.60	0.55	0.63	0.44	0.67	0.55	0.52	0.58
β^{BEAR} 5		Excess return	0.58	0.64	0.53	0.76	0.48	0.51	0.80	0.64	0.59	0.51
β^{BEAR} 6		Excess return	0.55	0.61	0.63	0.50	0.64	0.53	0.63	0.63	0.60	0.56
β^{BEAR} 7		Excess return	0.43	0.58	0.62	0.56	0.57	0.47	0.45	0.45	0.42	0.64
β^{BEAR} 8		Excess return	0.42	0.55	0.39	0.34	0.19	0.30	0.52	0.24	0.30	0.43
β^{BEAR} 9		Excess return	0.51	0.58	0.40	0.48	0.20	0.23	0.41	−0.03	0.40	0.37
β^{BEAR} 10		Excess return	0.12	0.07	−0.05	−0.21	−0.34	−0.14	0.01	−0.58	−0.11	0.11
β^{BEAR} 10 − 1		Excess return	−0.68	−0.75	−0.94	−1.10	−1.18	−1.02	−0.93	−1.53	−0.94	−0.80
			(−3.44)	(−3.27)	(−2.35)	(−2.35)	(−2.33)	(−2.43)	(−2.44)	(−2.58)	(−2.69)	(−2.35)
β^{BEAR} 10 − 1	CAPM	α	−0.78	−0.92	−1.28	−1.44	−1.47	−1.28	−1.25	−1.86	−1.17	−1.02
			(−4.15)	(−4.13)	(−3.18)	(−3.00)	(−3.01)	(−2.99)	(−3.58)	(−3.67)	(−3.77)	(−2.99)
β^{BEAR} 10 − 1	FF3	α	−0.76	−0.90	−1.16	−1.32	−1.31	−1.17	−1.15	−1.30	−1.11	−0.94
			(−4.00)	(−4.64)	(−4.78)	(−4.14)	(−4.35)	(−4.31)	(−4.59)	(−3.27)	(−4.58)	(−3.57)
β^{BEAR} 10 − 1	FFC	α	−0.79	−0.90	−1.06	−1.22	−1.24	−1.16	−1.04	−1.31	−1.00	−0.92
			(−3.67)	(−3.90)	(−3.87)	(−3.39)	(−3.84)	(−4.03)	(−3.62)	(−2.88)	(−3.59)	(−3.05)
β^{BEAR} 10 − 1	Q	α	−0.70	−0.81	−0.75	−0.88	−0.91	−0.75	−0.76	−1.07	−0.68	−0.70
			(−3.21)	(−3.51)	(−3.35)	(−2.86)	(−3.43)	(−2.93)	(−2.96)	(−2.61)	(−2.52)	(−2.66)
β^{BEAR} 10 − 1	FF5	α	−0.71	−0.79	−0.68	−0.82	−0.78	−0.60	−0.72	−0.89	−0.64	−0.64
			(−3.48)	(−4.19)	(−3.29)	(−3.55)	(−3.15)	(−2.27)	(−3.19)	(−2.56)	(−2.27)	(−2.75)
β^{BEAR} 10 − 1	FF5	β_{MKT}	0.06	0.15	0.25	0.23	0.27	0.15	0.25	0.06	0.24	0.17
			(1.21)	(1.96)	(2.95)	(2.39)	(2.44)	(1.73)	(2.33)	(0.49)	(2.41)	(2.63)
β^{BEAR} 10 − 1	FF5	β_{SMB_5}	0.38	0.42	0.32	0.35	0.29	0.44	0.35	0.34	0.33	0.15
			(4.59)	(4.70)	(2.47)	(2.22)	(1.67)	(3.88)	(2.63)	(2.03)	(2.55)	(1.32)
β^{BEAR} 10 − 1	FF5	β_{HML}	−0.29	−0.15	−0.15	−0.14	−0.24	−0.22	−0.15	−0.48	0.07	−0.12
			(−2.02)	(−0.84)	(−0.74)	(−0.73)	(−0.98)	(−1.06)	(−0.63)	(−2.07)	(0.28)	(−0.67)
β^{BEAR} 10 − 1	FF5	β_{RMW}	−0.10	−0.05	−0.61	−0.58	−0.50	−0.62	−0.52	−0.50	−0.37	−0.44
			(−0.70)	(−0.28)	(−2.14)	(−1.95)	(−1.63)	(−2.15)	(−1.92)	(−1.74)	(−1.47)	(−1.95)
β^{BEAR} 10 − 1	FF5	β_{CMA}	−0.03	−0.36	−0.87	−1.01	−1.01	−0.92	−0.81	−0.93	−1.08	−0.47
			(−0.14)	(−1.16)	(−2.65)	(−2.91)	(−2.70)	(−2.61)	(−2.18)	(−2.35)	(−2.83)	(−1.97)
Panel C: Large Cap sample												
β^{BEAR} 1		Excess return	0.73	0.75	0.88	0.79	0.82	0.80	0.86	0.85	0.80	0.86
β^{BEAR} 2		Excess return	0.68	0.59	0.80	0.88	0.70	0.69	0.86	0.87	0.78	0.93
β^{BEAR} 3		Excess return	0.61	0.60	0.69	0.75	0.63	0.54	0.73	0.70	0.52	0.68
β^{BEAR} 4		Excess return	0.58	0.58	0.73	0.63	0.66	0.51	0.68	0.61	0.61	0.52
β^{BEAR} 5		Excess return	0.59	0.64	0.46	0.60	0.65	0.52	0.68	0.62	0.53	0.65
β^{BEAR} 6		Excess return	0.51	0.63	0.64	0.58	0.53	0.59	0.64	0.70	0.45	0.50
β^{BEAR} 7		Excess return	0.59	0.62	0.61	0.48	0.54	0.45	0.61	0.29	0.53	0.69
β^{BEAR} 8		Excess return	0.45	0.48	0.35	0.43	0.18	0.22	0.42	0.38	0.35	0.41
β^{BEAR} 9		Excess return	0.51	0.52	0.42	0.35	0.17	0.23	0.42	−0.02	0.37	0.30
β^{BEAR} 10		Excess return	0.25	0.26	0.09	−0.06	−0.30	−0.07	0.02	−0.34	−0.11	0.30
β^{BEAR} 10 − 1		Excess return	−0.47	−0.48	−0.79	−0.85	−1.11	−0.87	−0.83	−1.18	−0.91	−0.56
			(−2.39)	(−2.42)	(−1.86)	(−2.15)	(−2.28)	(−2.06)	(−2.44)	(−2.15)	(−2.62)	(−1.84)
β^{BEAR} 10 − 1	CAPM	α	−0.59	−0.64	−1.09	−1.15	−1.38	−1.11	−1.15	−1.50	−1.13	−0.77
			(−3.17)	(−3.44)	(−2.51)	(−2.84)	(−2.83)	(−2.49)	(−3.48)	(−2.97)	(−3.60)	(−2.49)
β^{BEAR} 10 − 1	FF3	α	−0.56	−0.61	−0.98	−1.03	−1.21	−0.99	−1.04	−0.95	−1.01	−0.69
			(−3.09)	(−3.86)	(−3.61)	(−4.04)	(−3.97)	(−3.33)	(−4.65)	(−2.95)	(−4.46)	(−2.98)
β^{BEAR} 10 − 1	FFC	α	−0.57	−0.55	−0.89	−0.95	−1.15	−1.00	−0.94	−1.00	−0.91	−0.68
			(−2.90)	(−3.28)	(−2.93)	(−3.45)	(−3.89)	(−3.31)	(−4.10)	(−2.83)	(−3.76)	(−2.60)
β^{BEAR} 10 − 1	Q	α	−0.50	−0.44	−0.55	−0.65	−0.85	−0.62	−0.70	−0.84	−0.63	−0.44
			(−2.46)	(−2.61)	(−2.27)	(−2.73)	(−3.36)	(−2.43)	(−3.54)	(−2.21)	(−2.55)	(−1.93)
β^{BEAR} 10 − 1	FF5	α	−0.52	−0.46	−0.48	−0.57	−0.72	−0.45	−0.66	−0.58	−0.57	−0.39
			(−2.67)	(−2.84)	(−2.23)	(−3.00)	(−2.75)	(−1.86)	(−3.24)	(−1.99)	(−2.08)	(−1.83)
β^{BEAR} 10 − 1	FF5	β_{MKT}	0.12	0.15	0.20	0.20	0.26	0.15	0.28	0.09	0.26	0.17
			(2.42)	(2.95)	(2.63)	(2.35)	(2.98)	(1.86)	(2.80)	(0.72)	(2.60)	(3.20)
β^{BEAR} 10 − 1	FF5	β_{SMB_5}	0.23	0.22	0.20	0.26	0.17	0.30	0.26	0.23	0.16	0.12
			(3.54)	(2.51)	(1.33)	(1.79)	(1.08)	(2.36)	(1.98)	(1.44)	(1.15)	(1.21)
β^{BEAR} 10 − 1	FF5	β_{HML}	−0.25	−0.07	−0.10	−0.14	−0.27	−0.21	−0.15	−0.48	−0.00	−0.15
			(−2.10)	(−0.49)	(−0.54)	(−0.78)	(−1.21)	(−1.12)	(−0.78)	(−2.03)	(−0.02)	(−0.98)
β^{BEAR} 10 − 1	FF5	β_{RMW}	−0.12	−0.16	−0.70	−0.57	−0.54	−0.62	−0.44	−0.48	−0.32	−0.43
			(−0.90)	(−1.15)	(−2.53)	(−2.09)	(−1.83)	(−2.20)	(−1.74)	(−1.53)	(−1.27)	(−2.09)
β^{BEAR} 10 − 1	FF5	β_{CMA}	0.04	−0.34	−0.77	−0.84	−0.80	−0.81	−0.76	−0.81	−1.03	−0.44
			(0.25)	(−1.68)	(−2.80)	(−2.58)	(−2.66)	(−2.72)	(−2.45)	(−2.24)	(−2.86)	(−2.07)

to expected stock returns.[25] Table 6 shows that, as expected, β^{VOL} and β^{JUMP} have positive cross-sectional relations with β^{BEAR}. The positive relations between β^{BEAR} and each of $\beta^{\Delta\text{VIX}}$, β^{VOL}, and β^{JUMP} make it plausible that one or more of these variables explains the relation between β^{BEAR} and future stock returns. The results in Table 7, however, provide little evidence that any of these risk measures fully captures the pricing effect of β^{BEAR}, because the average returns and all alphas of the bivariate β^{BEAR} $10-1$ portfolios that are neutral to $\beta^{\Delta\text{VIX}}$, β^{VOL}, or β^{JUMP} are greater in magnitude than -0.45% per month in all three samples. The average returns and alphas are all significant at the 5% level except for the FF5 alphas when controlling for β^{JUMP} in the All Stocks and Large Cap samples, which are significant at the 10% level.

We then examine two measures of systematic skewness risk. While skewness does not explicitly differentiate between upside and downside risk, skewness risk could be mostly driven by the left-tail of the distribution of the market return. The first measure is coskewness (COSKEW), measured as the slope coefficient on MKT^2 from a 60-month rolling window regression of monthly excess stock returns on MKT and MKT^2, which is shown by Harvey and Siddique (2000) to be negatively related to expected stock returns.[26] Table 6 shows a positive cross-sectional relation between COSKEW and β^{BEAR}, suggesting that COSKEW could capture the β^{BEAR} effect. However, the results of the bivariate portfolio analysis show that controlling for COSKEW does not explain the negative average excess return or alphas of the β^{BEAR} $10-1$ portfolio. The second measure is skewness beta ($\beta^{\Delta\text{SKEW}}$) proposed in Chang et al. (2013), calculated as the slope coefficient on aggregate risk-neutral skewness innovations from a regression of daily excess stock returns on daily values of MKT and innovations in aggregate risk-neutral volatility, skewness, and kurtosis.[27] Chang et al. (2013) show that $\beta^{\Delta\text{SKEW}}$ is negatively related to expected stock returns. One would expect β^{BEAR} to be negatively correlated with the Chang et al. (2013) $\beta^{\Delta\text{SKEW}}$ because, all else equal, an increase in bear market risk likely corresponds to a decrease in risk-neutral skewness. Consistent with this prediction, Table 6 shows that stocks with high values of β^{BEAR} tend to have low values of $\beta^{\Delta\text{SKEW}}$. The negative correlation between β^{BEAR} and $\beta^{\Delta\text{SKEW}}$, combined with the fact that both variables negatively predict future stock returns, suggests that controlling for $\beta^{\Delta\text{SKEW}}$ is unlikely to explain the negative cross-sectional relation between β^{BEAR} and future stock returns. The results in Table 7 show that the average excess return and alphas of the bivariate β^{BEAR} $10-1$ portfolios constructed to be neutral to $\beta^{\Delta\text{SKEW}}$ remain negative, large in magnitude and, with a few exceptions, statistically significant. The exceptions are the Q and FF5 model alphas in the All Stocks sample of -0.85% (t-statistic $= -1.64$) and -0.58% (t-statistic $= -1.54$) per month, respectively, which are economically large but statistically insignificant at the 5% level. We attribute the lower significance to the abbreviated sample period from 1997 to 2007 for which $\beta^{\Delta\text{SKEW}}$ is available.

Finally, we control for two risk measures that are computed directly from individual stock returns. First, Kelly and Jiang (2014) calculate tail beta (β^{TAIL}) by regressing monthly stock returns on lagged tail risk, which is measured from large daily losses on individual stocks, and find that β^{TAIL} is positively related to expected stock returns.[28] Table 6 shows that average values of β^{TAIL} tend to decrease across the deciles of β^{BEAR}. Because β^{BEAR} and β^{TAIL} are negatively correlated in the cross section and predict future stock returns in opposite directions, controlling for β^{TAIL} could explain the ability of β^{BEAR} to predict future stock returns. However, the results of the bivariate portfolio analyses in Table 7 show that, after controlling for β^{TAIL}, the β^{BEAR} $10-1$ portfolio still generates negative, economically large, and highly statistically significant average excess returns and alphas. The results indicate that the information content of β^{TAIL} and our β^{BEAR} is different. Second, Ang et al. (2006b) find that idiosyncratic volatility (IVOL), calculated as the standard deviation of the residuals from a one-month rolling window regression of daily excess stock returns on MKT, SMB, and HML, is negatively related to the cross section of future stock returns. Table 6 shows that average values of IVOL do not exhibit a strong cross-sectional relation with β^{BEAR} and, not surprisingly, the bivariate portfolio analysis results in Table 7 show that controlling for IVOL does not explain the negative relation between β^{BEAR} and future stock returns. With the exception of the average excess return and FF5 alpha in the Large Cap sample, which are significant at the 10% level, the average excess returns and alphas of the bivariate β^{BEAR} $10-1$ portfolios that are neutral to IVOL are all negative, economically large, and significant at the 5% level.

5.2. Fama–MacBeth regression analyses

Bivariate portfolio analysis allows us to control for the effect of one variable at a time when examining the relation between bear beta and expected stock returns. To

[25] We thank Martijn Cremers, Michael Halling, and David Weinbaum for providing us with daily JUMP and VOL factor returns. The JUMP and VOL factor data end on March 31, 2012. Thus, analyses using β^{JUMP} or β^{VOL} cover months t (return months $t+1$) from December 1996 (January 1997) through March 2012 (April 2012).

[26] Harvey and Siddique (2000) proxy for the market portfolio return using a value-weighted index constructed from stocks traded on the NYSE and Amex only, instead of the NYSE, Amex, and Nasdaq. In unreported results, we verify that our results are robust when using a market portfolio return constructed from only NYSE and Amex stocks.

[27] We thank Bo Young Chang, Peter Christoffersen, and Kris Jacobs for providing the risk-neutral moments used to calculate moment innovations. The risk-neutral moment data end on December 31, 2007. Thus, analyses using $\beta^{\Delta\text{SKEW}}$ cover months t (return months $t+1$) from December 1996 (January 1997) through December 2007 (January 2008). We use skewness beta computed from a one-month multivariate regression because it exhibits the strongest predictive power among the four skewness betas reported in Table 3 in Chang et al. (2013). As in Chang et al. (2013), we orthogonalize kurtosis innovations to skewness innovations prior to calculating $\beta^{\Delta\text{SKEW}}$.

[28] We thank Bryan Kelly and Hao Jiang for providing us with the TAIL time series used to calculate β^{TAIL}. The TAIL data end in December 2011, thus analyses using β^{TAIL} cover months t (return months $t+1$) from December 1996 (January 1997) through December 2011 (January 2012).

control for multiple potentially confounding effects simultaneously, we use FM regression analyses. Each month t, we run the cross-sectional regression

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta^{\text{BEAR}}_{i,t} + \mathbf{\Lambda_t X_{i,t}} + \epsilon_{i,t}, \tag{11}$$

where $R_{i,t+1}$ is stock i's month $t+1$ excess return, $\beta^{\text{BEAR}}_{i,t}$ is stock i's month t value of β^{BEAR}, and $\mathbf{X_{i,\,t}}$ is a vector of control variables for stock i measured at the end of month t. All independent variables are winsorized at the 0.5% and 99.5% levels on a monthly basis. Our main hypothesis predicts that stocks with higher bear betas earn lower average returns and thus the average regression coefficient on β^{BEAR} should be negative.[29] If the pricing effect of bear beta is distinct from the phenomena captured by the control variables, the coefficient on β^{BEAR} should remain negative when controls are included in the regression specification. Table 8 presents the time series averages of the monthly cross-sectional regression coefficients along with NW-adjusted t-statistics testing the null hypothesis that the time series average is equal to zero.

We begin with two baseline specifications. Specification 1 has β^{BEAR} as the only independent variable. The average coefficients on β^{BEAR} are −0.45 (t-statistic = −2.39), −0.67 (t-statistic = −2.69), and −0.80 (t-statistic = −2.84) in the All Stocks, Liquid, and Large Cap samples, respectively, each of which is negative and statistically significant. This is consistent with the univariate portfolio results and indicates a strong negative relation between bear beta and expected stock returns. We next control for exposure to CAPM market risk by including β^{CAPM} as the second independent variable (Specification 2). This specification is comparable to the bivariate portfolio analysis that controls for β^{CAPM}. Table 8 shows that, although the average coefficient on β^{BEAR} is slightly lower (compared with the univariate specification) when controlling for β^{CAPM}, it remains negative and highly statistically significant in all three samples. Thus, the negative cross-sectional relation between β^{BEAR} and future stock returns is not explained by exposure to market risk.

The remaining regression specifications augment Specification 2 by including additional controls. We add β^{-} in Specification 3, $\beta^{\Delta\text{VIX}}$ in Specification 4, β^{JUMP} and β^{VOL} in Specification 5, COSKEW in Specification 6, $\beta^{\Delta\text{SKEW}}$ in Specification 7, β^{TAIL} in Specification 8, and IVOL in Specification 9. In each of these specifications, the average coefficient on β^{BEAR} remains negative and statistically significant at the 5% level in all three samples, with the only exception being Specification 7 in the All Stocks sample, which produces an average coefficient on β^{BEAR} that is negative and significant at the 10% level. As discussed in Section 5.1, the decreased statistical significance is likely because values of $\beta^{\Delta\text{SKEW}}$ are available only for the 133 months from December 1996 through December 2007, thus limiting the power of the test. In the Liquid and Large Cap samples, the limited power of the test is overcome by a more negative average coefficient, resulting in larger t-statistics.

We next control simultaneously for all of the risk variables that are available for the entire sample period (β^{CAPM}, β^{-}, $\beta^{\Delta\text{VIX}}$, COSKEW, and IVOL) in Specification 10. Table 8 shows that, with all risk variables included as controls, the average coefficient on β^{BEAR} remains negative and highly statistically significant in all three samples. Consistent with the bivariate portfolio analyses, the FM regression results provide no evidence that other risk variables explain the negative relation between β^{BEAR} and future stock returns.

Finally, in Specification 11, in addition to the risk variables in Specification 10, we include firm-level characteristics that have previously been shown to be related to expected stock returns. We add SIZE (log of MKTCAP), the log of the book-to-market ratio (BM), momentum (MOM), illiquidity (ILLIQ), profitability (Y), and investment (INV) as additional control variables.[30] Adding the characteristic controls to the regression specification does not explain the negative relation between β^{BEAR} and future stock returns. In Specification 11, which contains the full set of controls, the average coefficients on β^{BEAR} are −0.38 (t-statistic = −3.56), −0.39 (t-statistic = −2.90), and −0.48 (t-statistic = −2.68) in the All Stocks, Liquid, and Large Cap samples, respectively, each of which remains highly significant. In untabulated results, we add short-term reversal (Jegadeesh, 1990) and the maximum daily return (Bali et al., 2011; Bali et al., 2017) to Specification 11 and show that our results are robust to the inclusion of these additional controls.

Our All Stocks sample regressions produce significant average coefficients on each of BM, ILLIQ, Y, $\beta^{\Delta\text{SKEW}}$, IVOL, SIZE, and INV, with signs that are consistent with previous research.[31] However, the average coefficients on each of β^{CAPM}, β^{-}, $\beta^{\Delta\text{VIX}}$, β^{JUMP}, β^{VOL}, COSKEW, β^{TAIL}, and MOM are statistically indistinguishable from zero. The insignificant coefficient on β^{CAPM} is consistent with previous research (Black et al., 1972; Fama and French, 1992; Frazzini and Pedersen, 2014; Bali et al., 2017) showing the anomalous result that CAPM beta does not predict future stock returns. As discussed throughout the paper, bear market risk is associated with the left tail of the future market return distribution and has a component that is orthogonal to the realized market return. Therefore, the pricing of bear market risk is plausibly distinct from the pricing of market risk. The insignificant coefficients on β^{-}, $\beta^{\Delta\text{VIX}}$, β^{JUMP}, β^{VOL}, COSKEW, β^{TAIL}, and MOM suggest that β^{BEAR} could subsume the predictive power of these variables. We investigate this conjecture by running the FM regression analyses without including β^{BEAR} in the regression specification. The results of these analyses (unreported) do not support this conjecture because excluding β^{BEAR} from the regression specifications has almost no impact on the average coefficients on the other regressors.

[29] Because β^{BEAR} is an imperfect estimate of a stock's exposure to bear market risk, the usual errors-in-variables concern applies. This biases our coefficients toward zero and against us finding significant results.

[30] BM is calculated as the natural log of the book value of equity, defined as in Fama and French (1992), divided by MKTCAP. MOM is the 11-month stock return in months $t-11$ through $t-1$ inclusive (skipping month t). INV is calculated following Fama and French (2015). Y is calculated following Ball et al. (2016).

[31] In unreported tests, we calculate Y following Fama and French (2015) and find that using this alternative profitability measure has no impact on the ability of β^{BEAR} to predict future returns, but the average coefficient on Y becomes insignificant.

To understand why β^{-}, $\beta^{\Delta VIX}$, β^{JUMP}, β^{VOL}, COSKEW, β^{TAIL}, and MOM are insignificant in our sample, we begin by replicating the original studies showing the predictive power for these variables and then progressively modify the methodology and the sample toward that used in our study. Here, we briefly describe the results of these analyses. More details are available upon request. The insignificance of β^{-}, β^{VOL}, and β^{JUMP} in our analyses is because, as discussed in the original studies, these variables are related to contemporaneous returns but do not predict future returns. COSKEW, $\beta^{\Delta VIX}$, β^{TAIL}, and MOM are significantly related to future returns in the time periods examined by the original studies, but the relations are insignificant in the shorter time period covered by our sample. In summary, we find no evidence that β^{BEAR} explains the pricing effects associated with any of the control variables. The insignificant coefficients on the control variables in our analyses are either consistent with previous work or explained by differences in the samples examined by our study and previous studies.

The main takeaway from the results in Table 8 is clear. A strong negative cross-sectional relation exists between bear beta and expected stock returns that is not explained by other variables known to predict the cross section of expected stock returns.

5.3. Predictive power beyond one month

Our next set of tests examines whether β^{BEAR} can predict stock returns beyond the one-month horizon. If the negative relation between β^{BEAR} and future stock returns does reflect a risk-based phenomenon, we expect the pricing effect to exist beyond the one-month horizon used in our previous tests. Furthermore, the persistence of the cross-sectional relation is important for large institutional investors who could require extended periods after calculating bear beta to accumulate large stock positions. We

Table 8

Fama and MacBeth regression analyses.

The table presents the results of Fama and MacBeth (1973) regressions of month $t+1$ excess stock returns on month t β^{BEAR} and control variables. The table presents the time series averages of the monthly cross-sectional regression coefficients. t-statistics, adjusted following Newey and West (1987) using 12 lags, are presented in parentheses. Also reported are the average adjusted R-squared (Adj. R^2) and the average number of observations (N). All independent variables are winsorized at the 0.5% and 99.5% level on a monthly basis. Each column presents results for a different regression specification. The specification that includes β^{JUMP} and β^{VOL} covers the 184 months t (return months $t+1$) from December 1996 (January 1997) through March 2012 (April 2012). The specification that includes $\beta^{\Delta SKEW}$ covers the 133 months t (return months $t+1$) from December 1996 (January 1997) through December 2007 (January 2008). The specification that controls for β^{TAIL} covers the 181 months t (return months $t+1$) from December 1996 (January 1997) through December 2011 (January 2012). All other specifications cover the 225 months t (return months $t+1$) from December 1996 (January 1997) through August 2015 (September 2015). Panels A, B, and C present results for the All Stocks, Liquid, and Large Cap samples, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: All Stocks sample											
β^{BEAR}	−0.45	−0.35	−0.36	−0.36	−0.43	−0.41	−0.36	−0.39	−0.33	−0.39	−0.38
	(−2.39)	(−2.37)	(−2.53)	(−2.47)	(−2.69)	(−2.94)	(−1.79)	(−2.73)	(−2.71)	(−3.51)	(−3.56)
β^{CAPM}		−0.15	−0.09	−0.15	−0.09	−0.14	−0.22	0.02	−0.13	−0.11	0.24
		(−0.57)	(−0.39)	(−0.58)	(−0.27)	(−0.55)	(−0.55)	(0.06)	(−0.53)	(−0.47)	(0.97)
β^{-}			−0.08							−0.02	−0.05
			(−0.46)							(−0.22)	(−0.50)
$\beta^{\Delta VIX}$				−0.02						−0.04	−0.04
				(−0.36)						(−1.08)	(−1.09)
β^{JUMP}					0.50						
					(0.82)						
β^{VOL}					0.32						
					(1.49)						
COSKEW						−0.01				−0.01	−0.00
						(−1.01)				(−1.17)	(−0.24)
$\beta^{\Delta SKEW}$							−0.01				
							(−2.07)				
β^{TAIL}								−0.00			
								(−0.46)			
IVOL									−0.14	−0.12	−0.24
									(−1.96)	(−1.73)	(−4.92)
SIZE											−0.15
											(−2.59)
BM											0.20
											(1.83)
MOM											0.00
											(0.70)
ILLIQ											0.00
											(4.98)
Y											1.34
											(5.53)
INV											−0.74
											(−3.55)
Intercept	0.85	0.97	0.99	0.97	0.88	1.03	1.03	0.87	1.25	1.26	2.03
	(1.98)	(2.44)	(2.54)	(2.45)	(1.89)	(2.61)	(2.23)	(1.83)	(3.55)	(3.59)	(3.88)
Adj. R^2	0.60%	2.23%	2.45%	2.36%	2.72%	2.33%	2.69%	2.74%	3.68%	4.04%	5.82%
N	4,779	4,779	4,779	4,778	5,053	4,363	5,459	4,290	4,778	4,362	3,903

(continued on next page)

Table 8 (*continued*)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel B: Liquid sample											
β^{BEAR}	−0.67	−0.50	−0.49	−0.50	−0.50	−0.53	−0.59	−0.49	−0.46	−0.46	−0.39
	(−2.69)	(−3.12)	(−3.08)	(−3.25)	(−3.15)	(−3.22)	(−3.13)	(−2.98)	(−3.06)	(−3.06)	(−2.90)
β^{CAPM}		0.07	0.18	0.09	0.20	0.10	0.10	0.25	0.17	0.22	0.13
		(0.17)	(0.46)	(0.22)	(0.42)	(0.26)	(0.17)	(0.55)	(0.48)	(0.62)	(0.40)
β^{-}			−0.16							−0.07	−0.13
			(−0.72)							(−0.37)	(−0.78)
$\beta^{\Delta VIX}$				−0.10						−0.13	−0.12
				(−1.37)						(−2.02)	(−1.85)
β^{JUMP}					0.13						
					(0.11)						
β^{VOL}					0.14						
					(0.55)						
COSKEW						−0.00				−0.00	−0.00
						(−0.38)				(−0.11)	(−0.33)
$\beta^{\Delta SKEW}$							−0.01				
							(−0.59)				
β^{TAIL}								−0.00			
								(−0.43)			
IVOL									−0.16	−0.14	−0.15
									(−2.14)	(−1.90)	(−2.50)
SIZE											−0.13
											(−2.12)
BM											0.11
											(1.25)
MOM											0.00
											(0.55)
ILLIQ											0.28
											(1.42)
Y											1.77
											(4.03)
INV											−0.38
											(−2.54)
Intercept	0.72	0.70	0.75	0.69	0.53	0.72	0.63	0.51	0.86	0.87	1.73
	(1.96)	(2.08)	(2.34)	(2.10)	(1.39)	(2.26)	(1.38)	(1.40)	(2.30)	(2.58)	(2.76)
Adj. R^2	1.37%	4.94%	5.43%	5.30%	6.14%	5.19%	6.01%	5.84%	5.93%	6.82%	9.58%
N	2,040	2,040	2,040	2,040	2,107	1,917	2,234	1,875	2,040	1,917	1,850
Panel C: Large Cap sample											
β^{BEAR}	−0.80	−0.63	−0.64	−0.61	−0.65	−0.64	−0.90	−0.60	−0.56	−0.55	−0.48
	(−2.84)	(−3.05)	(−3.14)	(−3.10)	(−3.84)	(−2.88)	(−3.79)	(−3.00)	(−2.84)	(−2.67)	(−2.68)
β^{CAPM}		0.11	0.32	0.13	0.26	0.12	0.30	0.24	0.16	0.29	0.34
		(0.25)	(0.75)	(0.31)	(0.53)	(0.29)	(0.49)	(0.52)	(0.43)	(0.74)	(0.90)
β^{-}			−0.25							−0.17	−0.34
			(−1.14)							(−0.80)	(−1.56)
$\beta^{\Delta VIX}$				−0.07						−0.10	−0.10
				(−0.71)						(−1.08)	(−0.99)
β^{JUMP}					−0.34						
					(−0.19)						
β^{VOL}					0.28						
					(0.89)						
COSKEW						−0.01				−0.01	−0.01
						(−0.95)				(−0.87)	(−1.60)
$\beta^{\Delta SKEW}$							−0.00				
							(−0.02)				
β^{TAIL}								−0.00			
								(−0.26)			
IVOL									−0.09	−0.05	−0.08
									(−1.14)	(−0.76)	(−1.31)
SIZE											−0.13
											(−2.16)
BM											0.16
											(2.16)
MOM											0.00
											(0.99)
ILLIQ											−0.02
											(−0.23)
Y											1.54
											(2.74)
INV											−0.18
											(−1.16)
Intercept	0.68	0.62	0.67	0.61	0.39	0.64	0.37	0.43	0.73	0.71	1.70
	(1.93)	(1.91)	(2.14)	(1.86)	(1.10)	(2.06)	(0.82)	(1.23)	(2.01)	(2.08)	(2.92)
Adj. R^2	2.12%	7.14%	7.84%	7.66%	9.00%	7.38%	8.91%	8.32%	8.01%	9.17%	12.49%
N	1,005	1,005	1,005	1,005	1,023	963	1,073	947	1,005	963	932

Table 9
Fama and MacBeth regression analyses: k-month-ahead returns.
The table presents the results of Fama and MacBeth (1973) regression analyses of the relation between future excess stock returns and β^{BEAR} and control variables. Each month t, we run a cross-sectional regression of month $t+k$ excess stock returns on β^{BEAR} and combinations of the control variables, for $k \in 2, 3, 4, 5, 6$. The table presents the time series averages of the monthly cross-sectional regression coefficients on β^{BEAR}. t-statistics, adjusted following Newey and West (1987) using 12 lags, testing the null hypothesis that the average coefficient is equal to zero, are presented in parentheses. Each column presents results for a different regression specification. The specifications used in Columns 1–11 correspond to the specifications used in the columns of Table 8. All independent variables are winsorized at the 0.5% and 99.5% level on a monthly basis. The row labeled "R_{t+k}" presents results using the k-month-ahead excess stock return as the dependent variable. The specification that includes β^{JUMP} and β^{VOL} covers the 184 months t from December 1996 through March 2012. The specification that includes $\beta^{\Delta SKEW}$ covers the 133 months t from December 1996 through December 2007. The specification that controls for β^{TAIL} covers the 181 months t (return months $t+1$) from December 1996 (January 1997) through December 2011 (January 2012). All other specifications cover the 225 months t from December 1996 through August 2015. Panels A, B, and C present results for the All Stocks, Liquid, and Large Cap samples, respectively.

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: All Stocks sample											
R_{t+2}	−0.54	−0.46	−0.48	−0.47	−0.61	−0.57	−0.48	−0.55	−0.40	−0.50	−0.45
	(−2.93)	(−3.13)	(−3.35)	(−3.15)	(−3.68)	(−3.94)	(−2.76)	(−3.89)	(−3.27)	(−4.20)	(−4.44)
R_{t+3}	−0.59	−0.52	−0.53	−0.51	−0.68	−0.63	−0.61	−0.66	−0.45	−0.55	−0.52
	(−3.22)	(−3.74)	(−3.93)	(−3.75)	(−4.28)	(−4.68)	(−3.79)	(−4.75)	(−4.04)	(−4.92)	(−4.99)
R_{t+4}	−0.62	−0.53	−0.54	−0.53	−0.62	−0.62	−0.57	−0.63	−0.46	−0.55	−0.47
	(−3.26)	(−3.64)	(−3.76)	(−3.66)	(−3.48)	(−4.34)	(−3.40)	(−3.79)	(−3.95)	(−4.62)	(−4.36)
R_{t+5}	−0.58	−0.50	−0.52	−0.50	−0.59	−0.58	−0.53	−0.58	−0.44	−0.51	−0.42
	(−3.04)	(−3.16)	(−3.29)	(−3.14)	(−2.91)	(−3.74)	(−2.96)	(−3.17)	(−3.49)	(−4.22)	(−3.87)
R_{t+6}	−0.58	−0.51	−0.52	−0.51	−0.61	−0.56	−0.66	−0.56	−0.45	−0.50	−0.41
	(−2.81)	(−2.96)	(−3.17)	(−3.01)	(−2.72)	(−3.55)	(−3.16)	(−2.88)	(−3.30)	(−4.26)	(−4.23)
Panel B: Liquid sample											
R_{t+2}	−0.75	−0.58	−0.61	−0.58	−0.68	−0.63	−0.66	−0.60	−0.52	−0.57	−0.48
	(−2.94)	(−3.37)	(−3.43)	(−3.40)	(−3.65)	(−3.56)	(−3.71)	(−3.29)	(−3.27)	(−3.38)	(−3.15)
R_{t+3}	−0.73	−0.54	−0.57	−0.53	−0.69	−0.58	−0.69	−0.58	−0.45	−0.51	−0.43
	(−2.70)	(−3.51)	(−3.45)	(−3.45)	(−3.72)	(−3.70)	(−4.29)	(−3.32)	(−3.22)	(−3.15)	(−3.02)
R_{t+4}	−0.73	−0.54	−0.55	−0.53	−0.62	−0.55	−0.63	−0.54	−0.48	−0.50	−0.39
	(−2.66)	(−3.16)	(−3.06)	(−3.18)	(−3.15)	(−3.23)	(−3.64)	(−2.73)	(−3.07)	(−2.95)	(−2.66)
R_{t+5}	−0.64	−0.45	−0.46	−0.45	−0.50	−0.46	−0.53	−0.40	−0.39	−0.40	−0.34
	(−2.45)	(−2.71)	(−2.78)	(−2.79)	(−2.36)	(−2.89)	(−2.94)	(−2.14)	(−2.64)	(−2.71)	(−2.61)
R_{t+6}	−0.67	−0.47	−0.48	−0.47	−0.55	−0.45	−0.69	−0.38	−0.43	−0.43	−0.34
	(−2.42)	(−2.66)	(−2.87)	(−2.87)	(−2.23)	(−2.74)	(−2.84)	(−1.87)	(−2.67)	(−3.06)	(−2.87)
Panel C: Large Cap sample											
R_{t+2}	−0.88	−0.72	−0.72	−0.70	−0.82	−0.74	−0.78	−0.78	−0.63	−0.63	−0.54
	(−2.87)	(−3.13)	(−3.12)	(−3.17)	(−4.09)	(−3.09)	(−3.08)	(−3.22)	(−2.86)	(−2.84)	(−2.94)
R_{t+3}	−0.74	−0.59	−0.64	−0.57	−0.73	−0.61	−0.77	−0.68	−0.53	−0.56	−0.48
	(−2.52)	(−3.51)	(−3.50)	(−3.41)	(−4.60)	(−3.51)	(−4.15)	(−4.04)	(−3.22)	(−3.10)	(−3.20)
R_{t+4}	−0.65	−0.48	−0.50	−0.46	−0.61	−0.47	−0.66	−0.58	−0.44	−0.42	−0.34
	(−2.40)	(−3.06)	(−2.93)	(−3.00)	(−3.56)	(−2.82)	(−3.68)	(−3.56)	(−2.79)	(−2.37)	(−2.29)
R_{t+5}	−0.64	−0.49	−0.52	−0.49	−0.61	−0.47	−0.64	−0.50	−0.46	−0.45	−0.39
	(−2.23)	(−2.81)	(−2.74)	(−2.91)	(−3.10)	(−2.83)	(−3.22)	(−2.75)	(−2.78)	(−2.64)	(−2.81)
R_{t+6}	−0.73	−0.56	−0.55	−0.53	−0.73	−0.48	−0.73	−0.59	−0.50	−0.43	−0.40
	(−2.23)	(−2.77)	(−2.63)	(−3.01)	(−2.70)	(−2.47)	(−2.77)	(−2.48)	(−2.62)	(−2.49)	(−2.73)

therefore repeat the FM regression analyses with the same 11 sets of independent variables that were used in Table 8, this time using excess stock returns in month $t+k$, for $k \in \{2, 3, 4, 5, 6\}$, as the dependent variable.

Table 9 presents the results from these regressions. To save space, we report only the average coefficients on β^{BEAR} and associated t-statistics. Full results are shown in Tables OA2–OA6 of the Online Appendix. The results show that, with one exception, all specifications generate a negative and highly significant average coefficient on β^{BEAR}. The exception is Specification 8 in the All Stocks sample using month $t+6$ excess returns as the dependent variable, which produces an average coefficient on β^{BEAR} of −0.38 that is marginally significant with a t-statistic of −1.87. The results indicate that the negative cross-sectional relation between β^{BEAR} and future stock returns is strong for at least six months into the future.

6. Robustness

This section demonstrates that the results are robust to using alternative bear beta definitions, excluding the financial crisis period, and using out-of-sample data.

6.1. Alternative bear beta definitions

To examine the impact of the empirical choices associated with the implementation of β^{BEAR}, we repeat the FM regression analyses in Section 5.2 using alternative bear beta definitions. Complete results are provided in Tables OA7–OA17 of the Online Appendix. To save space, Table 10 presents only the average coefficients on the alternative bear beta measures and associated t-statistics for the regression specification that includes the full set of risk and characteristic controls that are available for the full sample period. Except for using a different measure of bear beta,

Table 10

Fama and MacBeth regression analyses: robustness.

The table presents the results of Fama and MacBeth (1973) regression analyses of the relation between future excess stock returns and a measure of bear market risk exposure and control variables. The measures of bear market risk exposure include our main measure β^{BEAR} and the alternative measures $\beta^{BEAR}_{\sigma=20\%}$, $\beta^{BEAR}_{1\sigma}$, $\beta^{BEAR}_{0.5\sigma}$, β^{BEAR}_{2Month}, β^{BEAR}_{EW}, β^{BEAR}_{4Day}, β^{BEAR}_{3Day}, β^{BEAR}_{UnAdj}, β^{PUT}, and β^{CME}, as indicated in the column headers. Each month t we run a cross-sectional regression of month $t+1$ excess stock returns on the given bear market risk exposure measure and control variables: β^{CAPM}, β^{-}, $\beta^{\Delta VIX}$, COSKEW, IVOL, SIZE, BM, MOM, ILLIQ, Y, and INV. The regression specification is the same as Specification 11 in Table 8 except that the measure of bear market risk exposure is different. Each of these analyses cover the 225 months t (return months $t+1$) from December 1996 (January 1997) through August 2015 (September 2015), with a few exceptions. The column labeled "β^{BEAR} excluding crisis" presents results using the main measure of bear beta (β^{BEAR}) after removing return months from December 2007 through June 2009, the period identified by the National Bureau of Economic Research as recessionary, from the sample. The tests using β^{CME} cover months t (return months $t+1$) from December 1988 (January 1989) through either August 2015 (September 2015) or November 1996 (December 1996). The table presents the time series averages of the monthly cross-sectional regression coefficients on the bear market risk exposure measure. t-statistics, adjusted following Newey and West (1987) using 12 lags, testing the null hypothesis that the average coefficient is equal to zero, are in parentheses. All independent variables are winsorized at the 0.5% and 99.5% level on a monthly basis. Panels A, B, and C present results for the All Stocks, Liquid, and Large Cap samples, respectively.

β^{BEAR}	$\beta^{BEAR}_{\sigma=20\%}$	$\beta^{BEAR}_{1\sigma}$	$\beta^{BEAR}_{0.5\sigma}$	β^{BEAR}_{2Month}	β^{BEAR}_{EW}	β^{BEAR}_{4Day}	β^{BEAR}_{3Day}	β^{BEAR}_{UnAdj}	β^{PUT}	β^{BEAR} excluding crisis	β^{BEAR}_{CME} 198901 -201509	β^{BEAR}_{CME} 198901 -199612
Panel A: All Stocks sample												
−0.38	−0.33	−0.35	−0.26	−0.25	−0.37	−0.39	−0.34	−0.27	−0.25	−0.32	−0.32	−0.22
(−3.56)	(−3.07)	(−3.57)	(−3.40)	(−2.84)	(−3.58)	(−3.06)	(−2.62)	(−3.05)	(−2.31)	(−3.25)	(−3.87)	(−1.50)
Panel B: Liquid sample												
−0.39	−0.38	−0.35	−0.25	−0.24	−0.41	−0.41	−0.24	−0.35	−0.28	−0.31	−0.38	−0.31
(−2.90)	(−2.73)	(−3.12)	(−2.71)	(−2.52)	(−3.08)	(−2.63)	(−1.49)	(−3.02)	(−2.02)	(−2.48)	(−3.87)	(−1.94)
Panel C: Large Cap sample												
−0.48	−0.46	−0.38	−0.21	−0.36	−0.49	−0.49	−0.33	−0.40	−0.45	−0.44	−0.39	−0.15
(−2.68)	(−2.50)	(−2.75)	(−1.90)	(−2.95)	(−2.94)	(−2.44)	(−1.63)	(−2.40)	(−2.44)	(−2.53)	(−3.17)	(−0.84)

these regressions are identical to regression Specification 11 in Table 8, which uses our focal measure β^{BEAR}.

We start by investigating the impact of alternative definitions of bear market states. Instead of using VIX, we use a constant standard deviation of 20% to determine the bear region boundary ($\beta^{BEAR}_{\sigma=20\%}$). Table 10 shows that the negative relation between bear beta and future stock returns remains qualitatively unchanged when using $\beta^{BEAR}_{\sigma=20\%}$ as the measure of bear market risk exposure. Second, we examine the ability of bear beta to predict future stock returns when the bear region is defined as states in which the market excess return is more than one standard deviation ($\beta^{BEAR}_{1\sigma}$) or 0.5 standard deviations ($\beta^{BEAR}_{0.5\sigma}$) below zero, instead of 1.5 standard deviations as in β^{BEAR}. The results demonstrate a highly significant negative relation between $\beta^{BEAR}_{1\sigma}$ and future stock returns in all three samples. The relation between $\beta^{BEAR}_{0.5\sigma}$ and future returns is negative in all three samples, highly significant in the All Stocks and Liquid samples, and marginally significant in the Large Cap sample (t-statistic = 1.90). The magnitudes of the average coefficients on bear beta are substantially smaller when using $\beta^{BEAR}_{0.5\sigma}$ than when using $\beta^{BEAR}_{1\sigma}$ or β^{BEAR}. This is consistent with the notion that risks associated with large down moves are priced differently from risks associated with more moderate losses.

Next, we examine the impact of empirical choices intended to reduce the noise in our measurement of bear beta. First, we investigate whether using two-month options (β^{BEAR}_{2Month}) instead of one-month options to construct the AD Bear portfolio affects our results. Table 10 shows that β^{BEAR}_{2Month} has a negative and highly significant relation with future stock returns, although the average coefficients on β^{BEAR}_{2Month} are noticeably smaller than the corresponding coefficients on β^{BEAR}. This is consistent with the fact that two-month options are generally less liquid and thus are likely to have less informative prices than one-month options, resulting in a noisier measure of bear market risk. Second, we examine the impact of using equal weights (β^{BEAR}_{EW}) instead of dollar trading volume weights to construct the AD Bear portfolio. We find that this change does not materially affect our results. In all three samples, the average coefficient on β^{BEAR}_{EW} is of similar magnitude and statistical significance to that of β^{BEAR}. Third, we estimate regression Eq. (7) using four-day (β^{BEAR}_{4Day}) and three-day (β^{BEAR}_{3Day}) holding period returns, instead of five-day returns as in β^{BEAR}. The table shows that the negative relation between bear beta and future stock returns remains strong when β^{BEAR}_{4Day} is used as the measure of bear market risk exposure and is somewhat weaker, although still negative, when β^{BEAR}_{3Day} is used. This is consistent with option returns over very short holding periods being more susceptible to microstructure noise induced by the bid-ask spread and nonsynchronous trading, resulting in less accurate estimates of bear market risk exposure. We also report results using two-day and one-day returns in the Online Appendix. Consistent with the findings here, we find that the relation between bear beta and future stock returns remains negative in all cases but the statistical significance gets progressively weaker as shorter holding period returns are used. Fourth, we test the impact of not adjusting the OLS estimates of bear beta using the Bayesian shrinkage methodology (β^{BEAR}_{UnAdj}). The table shows that the predictive power of β^{BEAR}_{UnAdj} is highly significant across all three samples, but the magnitudes of the average coefficients are smaller than those of the Bayes-adjusted version, especially in the All Stocks sample. This is consistent with the intuition that correcting for estimation error is more important for illiquid and small stocks.

Finally, we examine the impact of dropping the short put position from the AD Bear portfolio and using only the long put position. In a state-contingent pricing framework, a put position is equivalent to positions in AD Bear portfolios with different strikes (i.e., different boundaries for bear market states). Therefore, returns of a put are closely related to AD Bear portfolio returns. Consistent with this economic intuition, Table 10 shows that stock-level sensitivity to a long put position (β^{PUT}) is negatively and significantly related to future stock returns. To our knowledge, this is the first paper to show the pricing implications of exposure to an index put option in the cross section of stock returns. Results presented in Table OA17 of the Online Appendix also demonstrate that while the coefficient on β^{PUT} is negative in all regression specifications, β^{PUT} is a less powerful predictor of future stock returns than β^{BEAR}, especially in the All Stocks and Liquid samples. This result is expected because option returns are driven not only by fundamental risks such as bear market risk, but also by temporary demand pressure (Garleanu et al., 2009). Because the AD Bear portfolio is long and short puts with different strikes, its price is less impacted than the price of any individual put by demand pressure that causes positively correlated deviations from fundamental values across strikes. As a result, β^{BEAR} is a more precise measure of bear market risk exposure than β^{PUT}.

In summary, the results in Table 10 indicate that the negative relation between bear beta and future stock returns is robust to alternative implementations of bear beta. As would be expected, the results are stronger for measures that are likely to more accurately measure bear market risk exposure.

6.2. The financial crisis period

The financial crisis of 2007–2009 represents a bear market state realization in our sample period. This was a period of extreme financial stress when several measures of risk reached previously unachieved levels. For example, the VIX, one of the key inputs to the construction of the AD Bear portfolio, reached an all-time high closing level of 80.86 on November 20, 2008. To examine whether the negative relation between β^{BEAR} and future stock returns is driven by the financial crisis period of 2007–2009, we remove the return months from December 2007 through June 2009, the period identified by the National Bureau of Economic Research as recessionary, from the sample and rerun the FM regressions. The column labeled "β^{BEAR} excluding crisis" in Table 10 demonstrates that removing the crisis period has very little impact on our results, indicating that our results are not driven by the financial crisis period. Table OA18 of the Online Appendix provides the complete set of results.

6.3. Out-of-sample test

In our final robustness tests, we extend the sample period by using S&P 500 futures options traded on the Chicago Mercantile Exchange. The CME data begin on January 4, 1988, when one-month serial options start trading and end on August 31, 2015.[32] We follow the procedure in Section 3.2 to construct the AD Bear portfolio from the CME options and use the resulting AD Bear excess returns to estimate CME option-based bear beta (β^{BEAR}_{CME}). We then repeat the FM regression analyses using β^{BEAR}_{CME} as the measure of bear market risk exposure. We follow Ang et al. (2006b) and use VXO instead of VIX during the period when VIX is not available, i.e., prior to 1990. The second-to-last column of Table 10 shows that using the extended sample period covering months t (return months $t+1$) from December 1988 (January 1989) to August 2015 (September 2015) has little impact on our results. In all three samples, the average coefficient on β^{BEAR}_{CME} is negative and highly significant. The last column of Table 10 shows results for return months $t+1$ from January 1989 through December 1996, a period that falls entirely before the period examined in our main tests. The average coefficient on β^{BEAR}_{CME} is -0.22 (t-statistic $= -1.50$) in the All Stocks sample, -0.31 (t-statistic $= -1.94$) in the Liquid sample, and -0.15 (t-statistic $= -0.84$) in the Large Cap sample. Consistent with our main analysis, the point estimates from this shorter sample period indicate a negative relation between β^{BEAR}_{CME} and future stock returns in all three samples, though the statistical significance is lower. Tables OA19 and OA20 of the Online Appendix provide the complete set of results for the FM regression analyses using β^{BEAR}_{CME}.

7. Conclusion

In summary, we examine the hypothesis that time variation in the probability of future bear market states, which we refer to as bear market risk, is a priced risk factor. We construct an economically intuitive option portfolio, AD Bear, that pays off \$1 in bear market states and nothing otherwise. The short-term returns of this portfolio capture bear market risk. The AD Bear portfolio generates an economically and statistically significant negative alpha relative to standard factor models. We test whether bear market risk is priced in the cross section of stocks by examining the relation between bear beta (stock-level sensitivity to AD Bear portfolio returns) and expected stock returns. Portfolio and regression analyses demonstrate that high–bear beta stocks, i.e., stocks that outperform when bear market risk increases, earn low average returns. This negative cross-sectional relation between bear beta and expected stock returns remains strong after controlling for a battery of previously shown risk- and characteristic-based pricing effects. Additional tests provide further support for a risk-based interpretation of our results. Portfolios sorted on bear beta exhibit strong cross-sectional variation in post-formation exposure to bear market risk, the negative relation between bear beta and future stock returns remains strong even when the sample is restricted to liquid and large cap stocks, and the return predictability persists for at least six months into the future. We conclude that

[32] We thank the anonymous referee for suggesting this test. The CME options are American and expire on the third Friday of each month. Daily settlement prices are obtained directly from the CME.

bear market risk exposure is priced in the cross section of stocks returns.

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