Bear Beta*

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First version: June 2016

This version: November 2016

Abstract

We construct an Arrow-Debreu state-contingent security – "AD Bear" – that pays off $1 in bad market states and zero otherwise. Short-term AD Bear returns capture bear market risk — uncertainty caused by time-variation in investors' assessment of future bad economic states. We find that bear market risk is negatively priced. Stocks with high exposure to bear market risk, i.e., high bear beta, earn average returns 1% per month lower than stocks with low bear beta. Importantly, bear beta predicts not only future stock returns but also future bear beta. Our results remain strong among large and liquid stocks and are robust to controlling for extant factors and anomaly variables.

Keywords: Arrow-Debreu State Prices, Bear Beta, Bear Market Risk, Downside Risk, Factor Models
JEL Classifications: G11, G12, G13, G17

*We thank Robert Hodrick for earlier discussions on downside risk that inspired this project. We thank Vikas Agarwal, Turan Bali, Pierre Collin-Dufresne, Mehdi Haghbaali, John Hund, Dalida Kadyrzhanova, Haim Kassa, Lars Lochstoer, Narayan Naik, Bradley Paye, Chip Ryan, Jessica Wachter, Yuhang Xing, Baozhang Yang, Xiaoyan Zhang, and seminar participants at the 2016 All Georgia Conference, Georgia State University, the University of Georgia, Arizona State University, Fidelity Management and Research, JP Morgan Investment Management, MFS Investment Management, RBC Global Asset Management, State Street Global Advisors, and T. Rowe Price for their insightful comments that have substantially improved the paper.

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1 Introduction

Investors are known to be particularly averse to bear market states – states in which the market portfolio suffers a large loss.[1] As investors update their assessment of the prospect of future bear market states, security prices adjust accordingly. We refer to this time-variation in investors' ex ante assessment of future bear market states as "bear market risk". Recent theoretical work (Gabaix (2012) and Wachter (2013)) demonstrates that bear market risk is important in explaining time-series patterns in the market return. In these models, bear market risk is priced differently from the Capital Asset Pricing Model market risk. If bear market risk is indeed a systematic risk factor, arbitrage pricing theory predicts that stocks with different sensitivities to bear market risk – bear betas – should command different expected returns.

The contribution of this paper is to empirically investigate the impact of bear market risk on the cross-section of expected stock returns. Our key innovation is to develop a measure of bear market risk. We construct an Arrow (1964) and Debreu (1959) (AD) portfolio – AD Bear – from S&P 500 index put options that pays off $1 when the market at expiration is in a "bear" state.[2] The price of the AD Bear portfolio is a forward-looking measure of the (risk-neutral) probability of bear states. When held until expiration, the AD Bear return is completely determined by whether or not the market is in a bear state. The short-term AD Bear return, however, captures the change in the probability of bear market states. We therefore use short-term AD Bear returns to proxy for bear market risk.

Our main hypothesis is that bear market risk carries a negative price of risk. Intuitively, an increase in the probability of a large market loss reduces investors' utility and increases marginal utility. Therefore, securities with high (low) bear betas, i.e. stocks that outperform (underperform) when the probability of bear market states increases, should earn low (high) average returns because

[1] Differentiating downside risk from upside risk can be traced back at least as far as Roy (1952) and Markowitz (1959). Loss aversion is modeled theoretically by Kahneman and Tversky (1979), Gul (1991),Barberis et al. (2001), and Routledge and Zin (2010). Empirical work by Ang, Chen, and Xing (2006), Bali, Cakici, and Whitelaw (2014), Lettau, Maggiori, and Weber (2014), and Chabi-Yo, Ruenzi, and Weigert (2015) finds evidence that downside market risk is priced differently than general market risk.

[2] In our main specification, we define bear states to be states in which the market portfolio excess return is 1.5 standard deviations below zero or lower. Constructing state-contingent claims from options is motivated by Breeden and Litzenberger (1978).

they hedge against (exacerbate) such utility decreases.

We first run Fama and MacBeth (1973, FM hereafter) regressions of month $t+k$ stock excess returns on their bear betas computed at the end of month t. We find a strong negative cross-sectional relation between bear beta and future stock returns for up to six months in the future.

We then form decile portfolios by sorting on bear beta and examine the future returns of the value-weighted bear-beta sorted portfolios. Consistent with the FM regression analyses, the average portfolio returns exhibit a strong decreasing pattern across bear-beta deciles. A value-weighted zero-investment portfolio that goes long the top bear-beta decile portfolio and short 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.

For our results to be supportive of a rational risk pricing hypothesis, it is necessary that our portfolios, which are sorted on historically estimated pre-formation bear betas, have strong variation in post-formation exposure to bear market risk. We therefore examine the post-formation sensitivity of the bear-beta sorted portfolios to bear market risk. We find that post-formation sensitivities show a similar trend as the pre-formation sensitivities. The spread in the post-formation exposure between the high- and low-bear beta portfolios is both economically and statistically significant.

To further distinguish the risk-factor explanation from a potential mispricing story, we repeat our FM regression and portfolio tests among liquid and large cap stocks for which arbitrage costs are substantially lower. We find similar, if not stronger, results in a liquid stock sample, which contains roughly the 2000 most liquid stocks, and in a large cap stock sample, which contains roughly the 1000 largest stocks by market capitalization. These findings reinforce our interpretation that there is a cross-sectional trade-off between bear market risk and expected returns.

In all of our tests, we are careful to differentiate the negative cross-sectional relation between bear beta and future returns from previously documented relations. Most notably, we control for extant downside and tail risk measures such as downside beta (Ang, Chen, and Xing (2006)), tail beta (Kelly and Jiang (2014)), and coskewness (Harvey and Siddique (2000)). We also control for sensitivities to other option-based aggregate risk factors, such as VIX beta (Ang et al. (2006)), jump or volatility beta (Cremers, Halling, and Weinbaum (2015)), aggregate skewness beta (Chang, Christoffersen, and Jacobs (2013)) as well as other known determinants of expected returns such as market capitalization (Banz (1981), Fama and French (1992)), book-to-market ratio (Basu (1983), Fama and French (1992)), momentum (Jegadeesh and Titman (1993)), liquidity (Amihud (2002)), and idiosyncratic volatility (Ang et al. (2006)). Our results are highly robust to controlling for these previously documented effects.

Our work builds on previous research on downside risk. Ang, Chen, and Xing (2006)'s seminal paper shows 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.[3] We extend this line of research by investigating an economically distinct type of downside risk. Ang et al. (2006)'s downside beta, originally proposed by Bawa and Lindenberg (1977), is designed to capture the covariance between the stock return and the market return when a bear state occurs. In contrast, bear beta is the covariance between the stock return and the innovation in the probability of *future* bear states. To illustrate the difference, consider bear market states caused by the outbreak of war. Downside beta measures how a stock's price reacts when a war actually occurs. In contrast, bear beta measures the effect of changes in the probability of war, as international tensions increase or decrease, on the stock's price, even if a war does not actually materialize.

Empirically, since bear beta is a forward-looking measure that captures stock return covariance with the changes in the probability of future bear states, it does not rely on bear state realizations. This offers two advantages relative to downside beta. First, bear beta is computed using the full time-series of data even when the definition of a bear state is restricted to more extreme outcomes.[4] Second, bear beta is not subject to the potential peso problem faced by downside beta arising from the fact that in periods of prosperity, even the lowest returns may not represent bear states.

Our paper also adds to the research that uses the forward-looking information in option prices

[3]Subsequent research follows this general theme. Bali, Cakici, and Whitelaw (2014) find that the left tail return covariance between individual stocks predicts future stock returns. Lettau, Maggiori, and Weber (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, Ruenzi, and Weigert (2015) find that stocks that underperform during crashes generate higher average returns.

[4]In contrast, if a down state is defined as a market return that is 1.5 standard deviations or more below zero, consistent with our definition of a bear market state, downside beta is computed using only 6.7% of the available observations.

to investigate relations between aggregate risk and the cross section of expected stock returns.[5] Ang et al. (2006) and Cremers, Halling, and Weinbaum (2015) find that aggregate volatility risk is priced in the cross section of stock returns. Cremers, Halling, and Weinbaum (2015) examine contemporaneous relations between risk exposure and returns and find that jump risk is also priced. Not surprisingly, since AD Bear has positive vega and gamma exposure, bear beta has moderate cross-sectional correlations with Cremers, Halling, and Weinbaum (2015)'s volatility beta (vega exposure, correlation about 0.17) and jump beta (gamma exposure, correlation about 0.27). Including both volatility beta and jump betas as controls, however, has no impact on our results, indicating that we are capturing distinct pricing effects. Furthermore, in contrast to Cremers, Halling, and Weinbaum (2015), we focus on the predictive (instead of contemporaneous) relation between preformation risk exposure and post-formation returns, which has more practical value for portfolio choice decisions. Chang, Christoffersen, and Jacobs (2013) investigate whether innovations in the risk-neutral skewness of the market return is a risk factor and find a negative price of risk. Like volatility and jump risk, skewness reflects both the left tail and right tail of the distribution, while we focus solely on the left-tail distribution. Bear beta has almost zero cross-sectional correlation with Chang, Christoffersen, and Jacobs (2013)'s skewness beta, and inclusion of skewness beta as a control does not impact our results.

The remainder of this paper proceeds as follows. In Section 2 we develop the theoretical motivation for our main research question and implementation of our empirical analyses. Section 3 discusses how we create the AD Bear portfolio and examines it returns. In Section 4 we show that stock-level sensitivity to the AD Bear portfolio is priced in the cross section of stocks. Section 5 concludes.

[5] There is a separate line of research that uses returns of option portfolios to evaluate the non-linear risk exposure of hedge funds (Lo (2001), Mitchell and Pulvino (2001), Agarwal and Naik (2004), Jurek and Stafford (2015), Agarwal, Arisoy, and Naik (2016)). Another distinct line of work examines the ability of information embedded in single stock options (instead of sensitivities to the returns of index options) to predict future returns (Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010), Bali and Murray (2013), An et al. (2014)).

2 Theoretical Motivation for AD Bear

We begin by motivating AD Bear returns as a measure of bear market risk under Wachter (2013)'s time-varying rare disaster model. The benefit of doing so is a clear exposition of the relation between the pricing kernel, market risk, bear market risk, and AD Bear returns.

In Wachter (2013)'s model, the endowment (aggregate consumption, C_t) follows a jump-diffusion process

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

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 endowment 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. Bear market risk in this model is the innovation in the intensity of future jumps, or $dB_{\lambda,t}$, since λ_t is the sole state variable that determines time-variation in investors' assessment of future bear market states.

Letting π_t be the stochastic discount factor (SDF), F_t be the price of the market portfolio, and X_t be the price of the AD Bear portfolio, Table 1 examines the exposures of the SDF, F_t, and X_t to the three sources of risk.[6] The subsequent discussions focus on the first-order effects of the three shocks. In our empirical analyses we are careful to control for potential exposure to higher-order effects.

The sensitivity of the SDF to dB_t (continuous consumption innovations) is the negative of the coefficient of risk aversion ($-\gamma$). Intuitively, a positive consumption innovation decreases marginal utility. The sensitivity of the SDF to negative jumps in consumption is $-\gamma Z_t$. Finally, the SDF's sensitivity to bear market risk, captured by the innovations in the intensity of jumps, $dB_{\lambda,t}$, is $b_{\pi,\lambda}$

[6] All derivations are shown in Appendix A.

which is greater than zero since an increase in the intensity of jumps increases marginal utility.

We now examine the market portfolio return. The most important observation from Table 1 is that while both the market return and the SDF are sensitive to all three sources of risk, the SDF is not a linear function of the market return. Specifically, the sensitivities of the market return to the continuous consumption innovations (dB_t) and realized jumps (Z_t) are proportional to the corresponding SDF sensitivities, while the market return's sensitivity to innovations in jump intensity ($dB_{\lambda,t}$) is not. This means that in the economy described by Wachter (2013), the CAPM does not hold. The failure of the CAPM is driven by the sensitivity of the market portfolio's return to bear market risk, or innovations in jump risk intensity . To correctly price assets, therefore, one must account for the effect of bear market risk.

Table 1 shows that the sensitivities of the AD Bear portfolio's return to continuous consumption innovations (dB_t) and realized jumps (Z_t) are a simple multiple, $-\Delta$, of the market portfolio return's sensitivities to these risk factors. Therefore, a portfolio that is long one dollar of the AD Bear portfolio and long ΔX_t dollars of the market portfolio has zero exposure to continuous consumption innovations (dB_t) and realized jumps (Z_t). The returns of this portfolio are exposed only to bear market risk ($dB_{\lambda,t}$).

The relevant implications of the Wachter (2013) model are two-fold. First, bear market risk (captured in this model by time-variation in jump intensity) causes the CAPM to incorrectly price assets. Second, by hedging the exposure of the AD Bear portfolio to the market portfolio, we can capture bear market risk and examine the asset pricing implications of this source of risk.

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 expiring on the third Friday of each month, S&P 500 index levels, S&P 500 index dividend yields, VIX index levels, and risk-free rates for the period from January 4, 1996 through August 31, 2015 from OptionMetrics (OM).[7] 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 T-year 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 for maturity T, and y is the dividend yield of the index.

3.2 Construction of AD Bear

Theoretically, the AD Bear portfolio will generate 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. In practice, this payoff structure can only be approximated by a portfolio that is long a put option with strike price $K_1 > K_2$ and short a put option strike price K_2, as shown in Figure 1. The terminal payoff is $K_1 - K_2$ when the index level is below K_2 at option expiration, zero when the index level is above K_1, and linearly decreasing from $K_1 - K_2$ to zero when the index level is between K_2 and K_1. To make the terminal payoff equal to one when the index level is below K_2, we normalize the long and short put positions by $\frac{1}{K_1 - K_2}$.

When implementing the AD Bear portfolio, we make several empirical choices that are largely driven by features of the option data. First, for any day d, we create the AD Bear portfolio using one-month options, which are defined as options that expire in the calendar month subsequent to the calendar month in which day d falls. This choice is driven by the fact that one-month options tend to be more liquid than options with longer time to expiration.[8] Second, we choose K_2 to be 1.5 standard deviations below the forward price for the S&P 500 index with delivery on the same date that the options expire. 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

[7] On 1/31/1997 and 11/26/1997, no VIX index level is available. We set the VIX index level on 1/31/1997 to 19.47, its closing value on 1/30/1997. Similarly, we set the VIX index level on 11/26/1997 to 28.95, its closing value on 11/25/1997.

[8] The use of one-month options is consistent with previous research (Chang, Christoffersen, and Jacobs (2013), Cremers, Halling, and Weinbaum (2015), Jurek and Stafford (2015)). In unreported tests, we find that our results are robust when using two-month options.

deviations based on a trade off between our objective of capturing the pricing effect of severe bear states with the practical consideration that very-far OTM put options are illiquid, making their pricing unreliable and frequently unavailable in the data.[9] Third, following Jurek and Stafford (2015), we take the level of the VIX index divided by 100 as our measure of standard deviation.[10] Fourth, we choose K_1 to be 1 standard deviations below the forward price. Theoretically, we would like to choose K_1 close to K_2 because, as can be seen in Figure 1, the payoff function of the option portfolio converges to the theoretical AD Bear payoff function as $K_1 - K_2$ approaches zero. However, as K_1 approaches K_2, the difference in the prices of the options approaches zero as well. Since the price of the AD Bear portfolio is simply the difference in the option prices scaled by the difference in strikes, if we choose K_1 very close to K_2, the informational content of the price difference is frequently overwhelmed by bid-ask spread-induced noise.

We therefore construct the AD Bear option portfolio as follows. Letting T be the time until option expiration, σ be the level of the VIX index divided by 100, and F be the forward price, we define $K(z) = Fe^{z\sigma\sqrt{T}}$ to be the strike price z standard deviations from the forward price and $P(z)$ to be option price with strike $K(z)$. The price of the AD Bear portfolio, $P_{\text{AD Bear}}$, is

$$P_{\text{AD Bear}} = \frac{P(-1) - P(-1.5)}{K(-1) - K(-1.5)}. \tag{3}$$

Since options are available for only a discrete set of strikes, we approximate the price of the put option with strike price $K(z)$ as

$$P(z) = \sum_{z' \in [z-0.25,\ z+0.25]} P(z')w(z'). \tag{4}$$

The summation is taken over all traded options with strikes within 0.25 standard deviations of the target strike $K(z)$. The weight $w(z')$ is the ratio of the dollar trading volume of the option with strike price $K(z')$ to the total dollar volume of the options over which the summation is calculated:

[9] In unreported tests, we find that our results are slightly weaker when using one standard deviation below zero as the bear state boundary. The relative weakness is consistent with the market being more concerned about larger losses.

[10] In unreported tests, we find that our results are robust when using a constant standard deviation of 20%.

$$w\left(z'\right)=\frac{\$Vol\left(z'\right)}{\sum_{z'\in[z-0.25,\ z+0.25]}\$Vol\left(z'\right)} \tag{5}$$

where $\$Vol(z')$ is the dollar trading volume of the option with strike $K(z')$. 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.

3.3 AD Bear Portfolio Returns

Each trading day from January 4, 1996 through August 24, 2015, we create the AD Bear portfolio. We calculate the AD Bear return 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. But bear betas computed using short-term returns may suffer from biases introduced by nonsynchronous trading in the stock and option markets (Scholes and Williams (1977), Dimson (1979)). Using five-day returns is a reasonable balance between these two considerations.

The five-day excess return of the AD Bear portfolio formed five trading days prior to day d, which we denote $R_{\text{AD Bear},d}$, is given by

$$R_{\text{AD Bear},d}=\frac{P_{\text{AD Bear},d}-P_{\text{AD Bear},d-5}}{P_{\text{AD Bear},d-5}}-R_{f,d} \tag{6}$$

where $P_{\text{AD Bear},d}$ and $P_{\text{AD Bear},d-5}$ are the day d and $d-5$ prices, respectively, of the AD Bear portfolio formed at the close of day $d-5$, and $R_{f,d}$ is the five-trading day compounded gross return on the risk-free security from the close of day $d-5$ to the close of day d.[11] The result is a time-series of overlapping five-day excess returns of the AD Bear portfolio for the period from January 11, 1996 through August 31, 2015.[12]

[11]Daily risk-free security return data are gathered from Kenneth French's data library.

[12]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 . Since AD Bear has a non-negative payoff structure, we also require that entering into a long (short) position in the AD Bear portfolio by trading at the quoted bid and offer

Table 2 presents summary statistics for the daily five-day overlapping excess returns of the AD Bear portfolio. The first row presents results for the unscaled AD Bear returns. 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 weekly AD Bear excess returns reflects the embedded leverage of 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 excess market 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 return of −0.28% per five-day period with a standard deviation of 2.59. The distribution of AD Bear excess returns exhibits large positive skewness of 2.81.

The remainder of Table 2 presents, for comparison, summary statistics for the daily five-day excess returns of the market (MKT) factor, the size (SMB) and value (HML) factors of Fama and French (1993), the momentum (MOM) factor of Carhart (1997), the size (ME), profitability (ROE), and investment (IA) factors from the Q-factor model of Hou et al. (2015), and the size (SMB_5), profitability (RMW), and investment (CMA) factors from the five-factor model of Fama and French (2015).[13] 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 begin the empirical investigation of our main hypothesis by regressing AD Bear excess returns on standard risk factors AD Bear is positively exposed to bear market risk. If bear market risk carries a negative price of risk and is distinct from previously idenfied factors, then AD Bear should generate negative alpha relative to standard factor models. Before proceeding to the factor tests, we begin by examining whether the average AD Bear excess return is statistically distinguishable from zero. Table 3 shows that the average scaled AD Bear excess return of −0.28% per five-day

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would result in a positive cash outflow (inflow). Imposing these screens results in valid returns for 4910 out of 4944 days during the sample period.

[13]Daily 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 daily ME, ROE, and IA 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 compounded return of the risk-free security.

period is highly significant with a Newey and West (1987, NW hereafter)-adjusted t-statistic of -3.60.[14]

We then examine whether the premium earned by the AD Bear portfolio is compensation for CAPM market risk. This regression is particularly important because our theoretical motivation for AD Bear, derived in Section 2, predicts that while AD Bear returns are negatively correlated with market returns, AD Bear cannot be priced by CAPM. The AD Bear portfolio hedged with respect to market risk (hedged AD Bear) is positively exposed to bear market risk. Therefore, we expect the CAPM alpha of AD Bear to be negative. Table 3 shows that AD Bear's alpha relative to the CAPM model of -0.15% per five days is highly significant with a t-statistic of -3.83. This is our first indication of a negative price of bear market risk. As expected, AD Bear is strongly negatively exposed to the market factor, with a coefficient of -0.81. The adjusted R^2 from the regression indicates that approximately 35% of the variation in AD Bear excess returns cannot be explained by the market factor.

While the CAPM regression demonstrates that the negative premium generated by AD Bear is not completely explained by market risk, it is possible that some combination of previously established factors captures bear market risk. We therefore test whether AD Bear's CAPM alpha can be explained by established factor models. Table 3 shows that other factor models cannot explain the AD Bear excess returns. AD Bear produces alpha of -0.16% per five day period (t-statistic = -3.85) relative to the Fama and French (1993) model that includes MKT, SMB, and HML (FF3) and alpha of -0.14% per five day period (t-statistic of -3.23) relative to the four-factor model of Fama and French (1993) and Carhart (1997) (FFC) that includes MKT, SMB, HML, and MOM. AD Bear's alpha relative to the Q-factor model of Hou et al. (2015) (Q) that includes MKT, ME, ROE, and IA, is -0.13% per five day period (t-statistic of -3.09). Finally, AD Bear generates alpha of -0.13% (t-statistic = -2.97) per five-day period relative to the Fama and French (2015) five-factor model (FF5), which includes MKT, SMB_5, HML, RMW, and CMA. Augmenting the CAPM with additional factors produces negligible changes in R^2, suggesting that the hedged AD

[14] There is a substantial literature examining the large negative returns of out-of-the-money S&P 500 index put options (an incomplete list is Coval and Shumway (2001), Jackwerth (2000), Broadie, Chernov, and Johannes (2009), and Bondarenko (2014)). Our results are different because the AD Bear portfolio has both long and short positions in out-of-the-money put options.

Bear returns do not comove with these factors.

Since hedged AD Bear returns are theoretically related to bear market risk, we expect large hedged AD Bear returns to correspond to economic events that affect investors' forward-looking assessment of future bear market states. Figure 2 presents the time-series of hedged AD Bear returns. The largest residual of 34.62% occurs for the AD Bear portfolio formed at the close of trading on February 26, 2007, for which the return is calculated on 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 10 years.[15] The second largest residual of 16.8% comes on 5/6/2010 (formation date 4/29/2010). This period coincides with the 2010 Flash Crash and the opening of the criminal investigation of Goldman Sachs related to security fraud in mortgage trading.[16] The third largest residual occurs between 5/31/2011 and 6/7/2011, a period characterized by a series of bad economics 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 (8/18/2015 through 8/25/2015) corresponds to the Chinese stock market's "Black Monday" when the Shanghai Composite Index tumbled 8.5%, the biggest loss since February 2007. The fifth largest residual comes from 12/29/2014 through 1/6/2015, 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. As expected, the largest AD Bear residuals appear to be associated with important negative economic news, suggesting that AD Bear returns are related to bear market risk.[17]

In summary, Table 3 demonstrates that AD Bear returns have a component that is orthogonal to the MKT factorand other commonly used factors that generates a negative, economically large,

[15] Quote from Wall Street Journal, Page C4, Today's Market: "Investor fear that pressured stocks also spilled into bond markets... the Dow Jones Industrial Average finished 416.02 points, or 3.3%, lower as part of a global sell-off that began with a pullback in China's red-hot stock market."

[16] Quotes from Wall Street Journal, Page C4, Today's Market: "A bad day in the financial markets was made worse by an apparent trading glitch, leaving traders and investors nervous and scratching their heads over how a mistake could send the Dow Jones Industrial Average into a 1,000 point tailspin." "Stocks tumbled Friday, capping the worst week since January, as news that Goldman Sachs Group is now the subject of a criminal probe prompted investors to sell financial shares."

[17] While the largest AD Bear residuals coincide with moderately large negative market returns, these are not the largest negative market returns periods, indicating that AD Bear returns contain information not captured by the market return.

and highly statistically significant return. Large residuals from the factor models correspond to periods of negative economic news, consistent with our intent that the AD Bear returns capture bear market risk that is not captured by the market factor. We caution, however, against relying on these results to conclude that bear market risk is a priced risk factor. The AD Bear portfolio is constructed from out-of-the-money put options that have wide bid-ask spreads. Trading the AD Bear portfolio by buying at the ask price and selling at the bid price would incur transaction costs that are an order of magnitude larger than the average AD Bear return. We therefore interpret the AD Bear returns simply as indicative of bear market risk.

4 Bear Beta and Expected Stock Returns

The results in Section 3 suggest that the negative alpha of the AD Bear portfolio is compensation for exposure to a priced risk factor orthogonal to the factors captured by the CAPM, FF, FFC, Q, and FF5 factor models. If this is the case, stock-level sensitivity to the AD Bear portfolio excess returns should exhibit a negative cross-sectional relation with expected stock returns. In this section, we test this hypothesis by examining the relation between bear beta measured at the end of month t and stock returns in month $t+1$.

4.1 Variables

We begin by defining the variables used in our cross-sectional analyses. Additional data used to calculate these variables come from CRSP and Compustat.

4.1.1 Bear Beta

For each stock i at the end of each month t, we run 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

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

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 $R_{\text{AD Bear},d}$ is the contemporaneous

AD Bear excess return.[18] The regression uses overlapping returns for five-day periods ending on days d in months $t-11$ through t, inclusive. We require at least 183 valid observations to estimate the regression, meaning the regression has 180 degrees of freedom. To minimize the estimation errors associated with the rolling-window regressions, we follow Fama and French (1997) and adjust the OLS coefficient using a Bayes shrinkage method. We use the shrinkage-adjusted value, which we denote β^{BEAR}, in our empirical analyses. The details are provided in Appendix B.

4.1.2 Future Stock Return

The dependent variable of interest, the one-month-ahead excess stock return, which we denote R_{t+1}, is the delisting-adjusted (Shumway (1997)) stock return minus the return on the one-month U.S. Treasury bill in month $t+1$, recorded in percent.[19]

4.1.3 Control Variables

In our multivariate tests, we control for several variables known to be related to the cross-section of expected returns. A more detailed description of the control variables is provided in Section I of the online appendix.

Sensitivity Variables:

Ang, Chen, and Xing (2006) show that downside beta, or market beta on below-average market return days, is positively related to expected stock returns. Ang et al. (2006) demonstrate that sensitivity to changes in VIX (ΔVIX) is negatively related to expected stock returns. Kelly and Jiang (2014) establish that tail beta, or sensitivity to aggregate tail risk, is negatively related to expected stock returns. Cremers, Halling, and Weinbaum (2015) demonstrate that sensitivities to aggregate volatility and jump risk are negatively related to expected stock returns. Chang, Christoffersen,

[18] 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. When calculating five-day excess stock returns ($R_{i,d}$), we require that a return from each of the five days be available.

[19] 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 OTC), 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%.

and Jacobs (2013) show that sensitivity to aggregate risk-neutral skewness is negatively related to expected stock returns. Harvey and Siddique (2000) show that coskewness, a measure of asymmetric systematic risk, is negatively related to expected stock returns. We control for these effects, as well as CAPM beta, using the following variables measured for each stock i at the end of month t.

CAPM beta (β^{CAPM}): β^{CAPM} is the slope coefficient from a one-year rolling window regression of daily excess stock returns on MKT.

Downside beta (β^{-}): β^{-} is the slope coefficient from a one-year rolling window regression of daily excess stock returns on MKT using only below-average MKT days.

VIX beta (β^{VIX}): β^{VIX} is the slope coefficient on ΔVIX from a one-month rolling window regression of daily excess stock returns on MKT and ΔVIX.

Tail beta (β^{TAIL}): β^{TAIL} is the slope coefficient on lagged aggregate tail risk from a 10-year rolling window regression of monthly excess stock returns on one-month-lagged aggregate tail risk, calculated following Kelly and Jiang (2014).

Jump Beta (β^{JUMP}): β^{JUMP} is the sum of the coefficients on contemporaneous and lagged JUMP factor returns from a one-year rolling window regression, as in Cremers, Halling, and Weinbaum (2015).[20]

Volatility Beta (β^{VOL}): β^{VOL} is calculated in the same manner as β^{JUMP} using the VOL factor returns instead of JUMP factor returns.

Skewness Beta ($\beta^{\Delta\mathrm{SKEW}}$): $\beta^{\Delta\mathrm{SKEW}}$ is the slope coefficient on ΔSKEW from a regression of daily excess stock returns on daily values of MKT, ΔVOL, ΔSKEW, and ΔKURT, calculated following Chang, Christoffersen, and Jacobs (2013).[21]

Coskewness (COSKEW): COSKEW is the slope coefficient on MKT^2 from a 60-month rolling

[20] 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).

[21] We thank Bo Young Chang, Peter Christoffersen, and Kris Jacobs for providing the ΔVOL, ΔSKEW, and ΔKURT factor data. The ΔVOL, ΔSKEW, and ΔKURT data end on December 31, 2007. Thus, analyses using $\beta^{\Delta\mathrm{SKEW}}$ cover months t (return months $t+1$) from December 1996 (January 1997) through December 2007 (January 2008). We use the skewness beta computed based on one-month multivariate regression because it exhibits the strongest predictive power among the four skewness betas reported in Table 3 of Chang, Christoffersen, and Jacobs (2013).

window regression of monthly excess stock returns on MKT and MKT^2.

4.1.4 Characteristic Variables:

We also control for the previously documented relations between expected stock returns and size (Banz (1981); Fama and French (1992)), value (Basu (1983), Fama and French (1992)), momentum (Jegadeesh and Titman (1993)), idiosyncratic volatility (Ang et al. (2006)), and illiquidity (Amihud (2002)) using the standard measures, defined as follows.[22]

Market Capitalization (MKTCAP and SIZE): MKTCAP is the number of shares outstanding times the stock price, recorded in \$millions. SIZE is the natural log of $1 + \text{MKTCAP}$.

Book-to-Market Ratio (BM): BM is the natural log of the ratio of book equity to market equity, calculated following Fama and French (1992).

Momentum (MOM): MOM is the stock return during the 11-month period from month $t - 11$ through $t - 1$, inclusive, recorded in percent.

Idiosyncratic Volatility (IVOL): IVOL is the standard deviation of the residuals from a one-month rolling window regression of daily excess stock returns on MKT, SMB, and HML.

Illiquidity (ILLIQ): ILLIQ is the absolute daily return measured in percent divided by the daily dollar trading volume in \$millions, averaged over all days in months $t - 11$ through t, inclusive.

4.2 Samples

We use three different samples, which we term the All Stocks, Liquid, and Large Cap samples, in our examination of the relation between bear beta and expected stock returns. Each month t, the All Stocks sample consists of all U.S.-based common stocks in the CRSP database that have a valid month t value of β^{BEAR}. The Liquid sample is the subset of the All Stocks sample with values of ILLIQ that are less than or equal to the 80th percentile month t ILLIQ value among NYSE stocks. Finally, the Large Cap sample is the subset of the All Stocks sample with values of MKTCAP that are greater than or equal to the 50th percentile value of MKTCAP among NYSE stocks. Our

[22] In unreported results, we find that our results are robust when controlling for reversal (Jegadeesh (1990)) and the MAX effect (Bali, Cakici, and Whitelaw (2011), Bali et al. (2016)).

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 on a full year's worth of data based on the period of data available from OptionMetrics for calculating AD Bear returns.

Table 4 Panel A presents the time-series averages of monthly cross-sectional summary statistics for β^{BEAR} , MKTCAP, and ILLIQ. In the average month, All Stock sample values of β^{BEAR} range from -1.67 to 2.05, with mean (0.06) and median (0.05) values that are very close to zero and a standard deviation of 0.40. The distribution of β^{BEAR} has a small positive skewness of 0.23. 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 198 (4.75). The All Stocks sample has, on average, 4787 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 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 2041 (1005) stocks in an average month. Time-series averages of monthly cross-sectional correlations between β^{BEAR} and each of the control variables are shown in Panel B. Correlations between β^{BEAR} and the control variables are generally small in magnitude. It is worth noting, however, that β^{BEAR} has a positive cross-sectional correlation with both $\beta^{\text{JUMP}}$and β^{VOL}. This is not surprising. $\beta^{\text{JUMP}}$and β^{VOL} measure exposure to option gamma risk and option vega risk, respectively. Since the AD Bear portfolio has long gamma and vega exposures, a positive cross-sectional correlation between β^{BEAR} and each of these variables is expected.

4.3 Relation Between Bear beta and Expected Stock Returns

We now proceed to test our main hypothesis of a negative cross-sectional relation between β^{BEAR} and expected stock returns.

4.3.1 Fama-MacBeth Regression Analyses

We begin our examination of the relation between bear beta and expected stock returns with Fama and MacBeth (1973, FM hereafter) regression analyses. Each month t, we run a cross-sectional regression of month $t+1$ excess stock returns on month t values of β^{BEAR} and, in some specifications, a set of control variables. The cross-sectional regression specification is

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t}^{\text{BEAR}} + \mathbf{\Lambda_t X_{i,t}} + \epsilon_{i,t} \tag{8}$$

where $\mathbf{X_{i,t}}$ 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.

If bear market risk is a priced factor, then, all else equal, we expect that stocks with higher exposure to bear market risk, i.e. higher bear betas, earn lower average returns. We test this hypothesis by examining the regression coefficient on bear beta in the average month. This coefficient measures the cross-sectional impact of bear market risk on expected stock returns after controlling for the impacts of all of the other variables included in the regression specification. Our hypothesis predicts a negative average coefficient on bear beta.

Table 5 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. The results of the FM regressions using the All Stocks sample are shown in Panel A. Regression specification (1), which includes only β^{BEAR} as an independent variable, finds a negative and statistically significant average coefficient of -0.46 on β^{BEAR} with a t-statistic of -2.27, indicating a strong negative cross-sectional relation between β^{BEAR} and future stock returns. When we benchmark against the CAPM model by controlling for β^{CAPM} in specification (2), the coefficient on β^{BEAR} is reduced to -0.36 but remains significant at the 5% level (t-statistic = -2.06). This is consistent with the notion that β^{BEAR} and market beta capture different risk exposures.

Ang, Chen, and Xing (2006) find a positive relation between downside beta (β^{-}) and average returns. As discussed in the introduction and in Section 2, β^{-} , which captures market beta when the market has a below-average return, and β^{BEAR}, which captures sensitivity to bear market risk, measure exposure to two economically distinct sources of risk. Given the negative (positive) relation between β^{BEAR} (β^{-}) and expected returns, for β^{-} to explain the negative relation between β^{BEAR} and expected stock returns, we would expect a negative correlation between β^{BEAR} and β^{-}. Instead, we observe a small positive correlation in the sample (see Table 4, Panel B). Nonetheless, we formally test whether β^{BEAR} and β^{-} play distinct roles in the cross-section of expected returns by including both β^{BEAR} and β^{-} as independent variables in the regressions.. The results in specification (3) of Table 5 demonstrate that when controlling for β^{-}, the coefficient on β^{BEAR} of -0.38 remains negative, large in magnitude, and highly significant with a NW-adjusted t-statistic of -2.21. Therefore, controlling the downside beta does not explain the negative relation between bear beta and expected stock returns.

We next investigate whether VIX beta (β^{VIX}), shown by Ang et al. (2006) to be negatively related to expected stock returns, explains our results. Since VIX is often viewed as a gauge of fear among investors, it is possible that high β^{BEAR} stocks also have high β^{VIX} and thus have low expected returns. The results do not support this conjecture. The correlation between β^{BEAR} and β^{VIX} is close to zero (Panel B of Table 4). More importantly, when we control for β^{VIX} in FM regression specification (4) of Table 5, we find that the average coefficient on β^{BEAR} is nearly the same as in the univariate specification, and remains highly significant with a NW-adjusted t-statistic of -2.36.

In specification (5) we control for the jump beta (β^{JUMP}) and volatility beta (β^{VOL}) of Cremers, Halling, and Weinbaum (2015), who argue that the pricing effect of β^{VIX} in Ang et al. (2006) is not only related to volatility risk but potentially also related to jump risk.[23] Consistent with the previous results, we find that the negative cross-sectional relation between β^{BEAR} and expected stock returns persists after controlling for β^{JUMP} and β^{VOL}, since the average coefficient of -0.51 remains highly statistically significant (t-statistic $= -2.21$).

We then investigate whether the tail beta measure of Kelly and Jiang (2014) (β^{TAIL}) explains the negative relation between β^{BEAR} and expected stock returns. Kelly and Jiang (2014) estimate the level of tail risk by aggregating large one-day losses on individual stocks. They then compute tail beta by running lead-lag regressions of future stock returns on the lagged level of tail risk. The cross-sectional correlation between β^{BEAR} and β^{TAIL} is essentially zero (Panel B of Table 4), indicating that these two variables capture different phenomena. Consistent with the correlation analysis, controlling for β^{TAIL} in the FM regression analysis (specification (6) of Table 5) has little effect on the coefficient on β^{BEAR}, which is -0.48 with a NW-adjusted t-statistic of -2.74.

[23] β^{JUMP} and β^{VOL} are only available through December 2012 because the jump and volatility factor data provided by Cremers, Halling, and Weinbaum (2015) end in 2012.

Next, we examine the effect of controlling for $\beta^{\Delta\text{SKEW}}$ on the relation between β^{BEAR} and expected stock returns. Since skewness measures the difference between the right and left tails of a distribution, if the results in Chang, Christoffersen, and Jacobs (2013) are primarily driven by the left tail, then it is plausible that β^{BEAR} and $\beta^{\Delta\text{SKEW}}$ are capturing exposure to a similar risk factor. Specification (7) in Panel A of Table 5 refutes this hypothesis, since the coefficient on β^{BEAR} remains negative and significant after controlling for $\beta^{\Delta\text{SKEW}}$.

In specification (8) of Table 5 we control for coskewness of Harvey and Siddique (2000), a measure of asymmetric systematic risk that is negatively related to expected stock returns. The negative cross-sectional relation between β^{BEAR} and subsequent returns remains strong, if not stronger, with a FM regression coefficient of −0.51 and a NW-adjusted t-statistic of −2.66.

In specification (9), we include all sensitivity variables as simultaneous controls.[24] We find that the average coefficient on β^{BEAR} of −0.42 remains negative and highly statistically significant with a t-statistic of −2.74. Finally, in specification (10), we include both the sensitivity variables and characteristic variables (SIZE, BM, MOM, IVOL, ILLIQ) as controls. The average coefficient on β^{BEAR} of −0.35 remains negative and highly statistically significant with a t-statistic of −3.31. The table demonstrates that, regardless of specification, the results are strikingly similar. The FM regression analyses indicate a strong negative cross-sectional relation between β^{BEAR} and future stock returns.

If the negative cross-sectional relation between bear beta and future stock returns is truly indicative of a risk pricing effect, we expect that the effect remains strong in large and liquid stocks. On the other hand, if the negative relation between bear beta and future stock returns captures mispricing, we would expect the relation to be weak or non-existent among large and liquid stocks where limits to arbitrage (Shleifer and Vishny (1997)) are unlikely to bind. To distinguish between the risk pricing and mispricing explanations, we repeat the FM regression analyses using our Liquid and Large Cap samples.

The results of the FM regressions using the Liquid sample, shown in Panel B of Table 5, are

[24]Since the jump and volatility factors provided by Cremers, Halling, and Weinbaum (2015) and risk-neutral skewness provided by Chang, Christoffersen, and Jacobs (2013) are not available for the full sample, we do not include β^{JUMP}, β^{VOL}, or $\beta^{\Delta\text{SKEW}}$ in specifications (9) and (10).

highly consistent with those from the All Stocks sample. In all specifications, the average slope on β^{BEAR} is negative and statistically significant, with values ranging from -0.36 to -0.89 and t-statistics greater than 2.30 in magnitude. Interestingly, in all specifications, the average coefficient on β^{BEAR} from the Liquid sample regressions is larger than the corresponding value from the All Stocks sample regressions. When using the Large Cap sample (Panel C), once again, regardless of specification, the average coefficient on β^{BEAR} is negative and highly significant. The Large Cap sample β^{BEAR} coefficients are substantially larger in magnitude than those of the other two samples, indicating that the negative relation between β^{BEAR} and future stock returns is not driven by small or illiquid stocks. The Liquid and Large Cap sample results are inconsistent with a mispricing story and provide strong evidence supporting our risk pricing hypothesis.

Another possible explanation for our results is that the negative relation between bear beta and future stock returns reflects a microstructure effect. One might argue that because the calculation of bear beta uses the return on the last trading day of month t and we examine the return from the close of month t to the close of month $t+1$, our results do not reflect attainable returns because it would not be possible to calculate bear beta and then execute a trade based on this signal. To ensure that our results are not due to a short-term microstructure effect, we repeat the FM regression analyses using excess stock returns in month $t+k$, for $k \in \{2, 3, 4, 5, 6\}$ as the dependent variable. The regression specifications are otherwise unchanged.

Table 6 presents the average coefficients on β^{BEAR} from these regressions (to save space, we do not report other coefficients, the one-month-ahead results are repeated for comparison). In all specifications and all samples, the average coefficient on AD Bear is negative and highly statistically significant. The results indicate that the negative cross-sectional relation between β^{BEAR} and future stock returns is strong for six months into the future.[25]

The main takeaway from the results in Table 5 is clear. There is a strong, economically important, negative cross-sectional relation between bear beta and expected stock returns. This relation is not explained by other variables known to predict the cross-section of expected stock returns. Furthermore, the relation appears to be similarly strong or stronger among liquid and large stocks,

[25] In unreported results, we find that the relation between β^{BEAR} and returns in month $t+7$ is negative but insignificant.

consistent with a risk-based interpretation.

4.3.2 Univariate Portfolio Analyses

We continue our examination of the relation between bear beta and expected stock returns with a univariate portfolio analysis using β^{BEAR} as the sort variable. Portfolio analysis allows us to examine the relation between β^{BEAR} and future stock returns without relying on the linearity assumption inherent in the FM regression procedure. 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 10 portfolio and short the β^{BEAR} decile one portfolio (β^{BEAR} $10-1$ portfolio).

Panel A of Table 7 shows that for the All Stocks sample, the β^{BEAR} decile one portfolio generates an average excess return of 0.99% per month while the average excess return of the 10th decile portfolio is -0.14% per month. The β^{BEAR} $10-1$ portfolio, therefore, generates an economically large and highly statistically significant negative average return of -1.13% per month with a NW t-statistic of -2.67. To examine whether the pattern in the excess returns of the β^{BEAR}-sorted portfolios is a manifestation of exposure to previously identified factors, we calculate the abnormal returns of the decile portfolios relative to several different factor models. The results demonstrate that the average return of the High$-$Low β^{BEAR} portfolio is not explained by any of these factor models. Specifically, the β^{BEAR} $10-1$ portfolio generates alpha of -1.48 per month (t-statistic $= -3.59$) relative to the CAPM risk model. This result indicates that risk exposure to AD Bear returns after controlling for market exposure is priced, consistent with our theoretical prediction. The β^{BEAR} $10-1$ portfolio's FF3 alpha of -1.33% (t-statistic $= -3.92$) and FFC alpha of -1.25% (t-statistic $= -3.38$) per month are similarly large and significant. When the returns of the High$-$Low β^{BEAR} portfolio are subjected to the Q and FF5 models, the alphas of -0.84% and -0.71% per month, while somewhat smaller in magnitude than the alphas relative to other risk models, are still economically large and highly statistically significant with a t-statistics of -2.41 and -2.29, respectively.

A factor model indicates contemporaneous relations between the true factor loading and expected returns. Our empirical tests have used a pre-formation measure of bear beta (β^{BEAR}) calculated at the end of month t to predict returns for month $t+1$ and implicitly assumed that this pre-formation β^{BEAR} is indicative of the month $t+1$ stock-level sensitivity to bear market risk. For our results to be supportive of risk factor interpretation, it is necessary that this assumption hold true. To test whether this is the case, we calculate the post-formation sensitivities of the decile portfolio returns to the AD Bear returns by regressing the entire time-series of post-formation overlapping five-day excess returns of the β^{BEAR} decile portfolios on the contemporaneous AD Bear excess return and MKT, as in equation 7.

For sake of comparison, Table 7 presents value-weighted (VW) and equal-weighted (EW) average values 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 first β^{BEAR} decile portfolio to 0.78 for β^{BEAR} decile portfolio 10. The post-formation decile portfolio sensitivities to AD Bear excess returns ($\beta_{\text{AD BEAR}}$) are shown at the bottom of Table 7. In support of the interpretation that bear market risk is a systematic risk factor, the results indicate that the β^{BEAR} $10-1$ portfolio has a strong positive post-formation AD Bear sensitivity of 0.21 (t-statistic = 2.83). 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. To our knowledge, this is the first paper to identify a factor not based on stock returns that successfully generates significant spreads in the post-formation returns and post-formation factor loadings among stock portfolios sorted on pre-formation factor sensitivities. The results are highly indicative of a rational risk-based explanation for the patterns in returns.

As with the FM regressions, we examine the possibility that our results are due to mispricing by repeating the portfolio tests using our Liquid and Large Cap samples. The portfolio analysis results for the Liquid sample, shown in Panel B of Table 7, are very similar to those of the All Stocks sample. The Liquid sample β^{BEAR} $10-1$ portfolio generates an economically large and highly statistically significant average return of -1.08% per month (t-statistic = -2.41). The alphas of this portfolio relative to the CAPM, FF3, FFC, Q, and FF5 factor models of -1.48% per month (t-statistic = -3.48), -1.33% per month (t-statistic = -4.02), -1.22% per month (t-statistic =

-3.38), -0.85% per month (t-statistic = -2.49), and -0.70% per month (t-statistic = -2.39) are also economically large and highly statistically significant. As was the case in the All Stocks sample, average excess returns of the Liquid sample decile portfolios are nearly monotonically decreasing across β^{BEAR} deciles. The Liquid sample pre-formation and post-formation AD Bear portfolio sensitivities are also extremely similar to those of the All Stocks sample. The Liquid sample β^{BEAR} $10-1$ portfolio has a post-formation sensitivity of 0.22 (t-statistic = 2.81) to the AD Bear Portfolio 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 Table 7 Panel C 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 economically large and highly statistically significant negative alpha relative to all factor models, and exhibits strong positive post-formation sensitivity to the AD Bear portfolio excess returns.

The returns of the value-weighted univariate portfolios presented in Table 7 are highly consistent with those of the FM regressions. Both the FM regression and portfolio analyses provide strong evidence that bear market risk carries a negative risk premium and plays an important role in determining the cross-section of expected stock returns.

4.3.3 Bivariate Portfolio Analyses

To further verify that the results of the portfolio analyses in Table 7 are not driven by a relation between β^{BEAR} and a previously identified stock return predictor, we examine the relation between β^{BEAR} and future stock returns using bivariate-sort portfolio analyses. The portfolios in these analyses are constructed to be neutral to a control variable while having variation in β^{BEAR}. At the end of each month t, we sort all stocks into ascending control variable deciles using breakpoints determined by all stocks in the sample under examination. Within each control variable decile, we 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. 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 β^{BEAR} decile portfolio return. Finally, we calculate the difference in month $t+1$ returns between the β^{BEAR} decile 10 and decile one portfolios (β^{BEAR} $10-1$ portfolio).

The results of the bivariate portfolio analyses are shown in Table 8. To conserve space, we only present results for the Liquid sample. Results for the other samples are similar. The table reports the time-series averages of the monthly excess returns for the average control variable decile within each decile of β^{BEAR}, as well as excess returns, alphas, and FF5 model sensitivities for the average High$-$Low β^{BEAR} portfolio. Regardless of which control variable is used, the excess returns show a strong decreasing pattern across β^{BEAR} deciles. In all cases, the average excess return and all alphas of the β^{BEAR} $10-1$ portfolio are negative, large in magnitude, and highly statistically significant. The results of the bivariate portfolio analyses demonstrate that the negative relation between β^{BEAR} and future stock returns is not driven by a relation between β^{BEAR} and any of the control variables.

5 Conclusion

In summary, we examine the hypothesis that time-variation in investors' ex ante assessment of future bear market states, which we refer to as bear market risk, is a priced risk factor. We construct a theoretically motivated option portfolio, AD Bear, that pays of \$1 in bear market states and \$0 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 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. Regression analyses detect a strong negative cross-sectional relation between bear beta and expected stock returns. Zero-investment portfolios that are long high-bear beta stocks and short low-bear beta stocks generate economically large and highly statistically significant negative average returns and alphas relative to standard factor models. Supportive of a risk-based interpretation of our results, the negative relation between bear beta and future stock returns remains strong even when the sample is restricted to liquid and large-cap stocks, the return predictability persists for at least six months into the future, and portfolios sorted on bear beta exhibit strong cross-sectional variation in post-formation exposure to AD Bear returns. Our results are robust after controlling for a battery of downside risk measures used in previous work, as well as other known predictors of stock returns. We conclude that bear market risk is a priced source of risk distinct from previously identified factors.

Appendix A AD Bear Portfolio Sensitivities

In this appendix, we derive the sensitivity of the AD Bear returns to continuous consumption innovations (dB_t), negative jumps in consumption (Z_t), and innovations in jump intensity ($dB_{\lambda,t}$).

Assuming a recursive utility function and that the market portfolio is a levered claim to aggregate consumption (i.e., dividend $D_t = C_t^{\phi}$), Wachter (2013) shows that the evolution of the price of the market portfolio, F_t, is given by

$$\frac{dF_t}{F_t} = \mu_{F,t}dt + \phi\sigma dB_t + b_{F,\lambda}\sigma_\lambda\sqrt{\lambda_t}dB_{\lambda,t} + (e^{\phi Z_t} - 1)dN_t, \tag{A.1}$$

and the evolution of the state price density π_t is defined by

$$\frac{d\pi_t}{\pi_{t^-}} = \mu_{\pi,t}dt - \gamma\sigma dB_t + b_{\pi,\lambda}\sigma_\lambda\sqrt{\lambda_t}dB_{\lambda,t} + (e^{-\gamma Z_t} - 1)dN_t \tag{A.2}$$

where ϕ is the market portfolio's leverage with respect to aggregate consumption, γ is the risk aversion parameter, and $b_{F,\lambda}$ and $b_{\pi,\lambda}$ are the sensitivities of the market return and the stochastic discount factor, respectively, to $dB_{\lambda,t}$. Because heightened jump intensity increases marginal utility and depresses stock prices, $b_{F,\lambda} < 0$ and $b_{\pi,\lambda} > 0$.

The AD Bear portfolio is defined to generate payoff X_T of \$1 at expiration date T if the time T price of the market portfolio is below a threshold identified by K. Specifically, $X_T = 1\left\{\frac{F_T}{F_0} \leq K\right\}$. Therefore, at any point in time $t < T$, the price of the AD Bear portfolio is given by

$$X_t = E_t^Q\left(e^{-\int_t^T r_\tau d\tau}1\left\{\frac{F_T}{F_0} \leq K\right\}\right) \tag{A.3}$$

where $E^{\mathbb{Q}}$ is the risk-neutral expectation function and r_s is the time s instantaneous risk-free rate.

While equation (A.3) can be solved using numerical methods, it does not have an analytical solution. We make two approximations to arrive at an approximate analytical solutionthat delivers transparent economic intuition.

Approximation 1: We assume the instantaneous risk-free rate r_t over the time interval from 0 to T is deterministic. In our empirical set-up, T is about 1 month after t and thus the approximation should be quite accurate. Under this assumption,

$$
\begin{aligned}
dX_t &= E^Q_{t+\Delta t}\left(1\left\{\frac{F_T}{F_0} \le K\right\}\right) e^{-r_t(T-t-\Delta t)} - E^Q_t\left(1\left\{\frac{F_T}{F_0} \le K\right\}\right) e^{-r_t(T-t)} \\
&= \left[E^Q_{t+\Delta t}\left(1\left\{\frac{F_T}{F_0} \le K\right\}\right) - E^Q_t\left(1\left\{\frac{F_T}{F_0} \le K\right\}\right)\right] e^{-r_t(T-t-\Delta t)} \\
&+ E^Q_t\left(1\left\{\frac{F_T}{F_0} \le K\right\}\right)\left(e^{-r_t(T-t-\Delta t)} - e^{-r_t(T-t)}\right) \\
&= \left[E^Q_{t+\Delta t}\left(1\left\{\frac{F_T}{F_0} \le K\right\}\right) - E^Q_t\left(1\left\{\frac{F_T}{F_0} \le K\right\}\right)\right] e^{-r_t(T-t-\Delta t)} + X_t\left(e^{r_t\Delta t} - 1\right) \qquad \text{(A.4)}
\end{aligned}
$$

Letting $P_t = E^Q_t\left(1\left\{\frac{F_T}{F_0} \le K\right\}\right)$ gives

$$
dX_t = dP_t e^{-r_t(T-t-\Delta t)} + X_t r_t \Delta t. \qquad \text{(A.5)}
$$

In the following analysis, we focus on the sensitivity of dP_t to the fundamental risks, which is closely related to the sensitivity of dX_t to the fundamental risks.

Under Wachter's model, $\frac{F_T}{F_0} = exp\left(\phi log\left(\frac{C_T}{C_0}\right) + b_{F,\lambda}\left(\lambda_T - \lambda_0\right)\right)$ (Seo and Wachter (2015)), giving

$$
P_t \quad = \quad E^Q_t\left(1\left\{\phi log\left(C_T\right) + b_{F,\lambda}\lambda_T \le log\left(K\right) + b_{F,\lambda}\lambda_0 + \phi log\left(C_0\right)\right\}\right) \qquad \text{(A.6)}
$$

Approximation 2: λ_T follows a CIR model and does not have a closed-form solution. However, over the short interval T, λ_T can be approximated by a Vasicek model with constant volatility and thus follows a normal distribution:

$$
\lambda_T \sim N\left(\left(1 - e^{-\kappa\tau}\right)\overline{\lambda} + \lambda_t e^{-\kappa\tau}, \frac{\sigma^2_\lambda \lambda_t}{2\kappa}\left(1 - e^{-2\kappa\tau}\right)\right). \qquad \text{(A.7)}
$$

Using these two approximations, we get an analytical solution.

$log\left(C_T\right)$ follows a normal distribution with mean $log\left(C_t\right) + \left(\mu - \frac{1}{2}\sigma^2\right)\tau$ and variance $\sigma^2\tau$ with

$\tau = T - t$ if there is no jump. We also assume Z_i is of constant size $\mu_Z < 0$. Following Merton (1976), we know that conditional on $N_T - N_t = n$

$$\phi log\left(C_T\right) + b_\phi \lambda_T \quad \sim \quad N\left(\mu_n, \nu^2\right) \tag{A.8}$$

where

$$\mu_n = \phi log\left(C_t\right) + \mu_c^Q\left(T\right) + \mu_\lambda^Q\left(T\right) + b_\phi \lambda_t e^{-\kappa(T-t)} + n\phi\mu_Z \tag{A.9}$$

and

$$\nu^2 = \phi^2\sigma^2 T + b_\phi^2 \frac{\sigma_\lambda^2 \lambda_t}{2\kappa}\left(1 - e^{-2\kappa T}\right) \tag{A.10}$$

where $\mu_\lambda^Q\left(\tau\right)$ and $\mu_c^Q\left(T\right)$ capture the drift terms unrelated to λ_t and $log\left(C_t\right)$, respectively, under the Q measure.

Therefore,

$$P_t \quad = \quad \sum_{n=0}^{\infty} \frac{e^{-\lambda_t(T-t)}\left(\lambda_t\left(T-t\right)\right)^n}{n!} N\left(d_n\right) \tag{A.11}$$

where

$$d_n = \frac{log\left(K\right) + b_\phi \lambda_0 + \phi log\left(C_0\right) - \mu_n}{\nu} = \frac{\eta_n}{\nu} \tag{A.12}$$

and $\eta_n = log\left(K\right) + b_\phi \lambda_0 + \phi log\left(C_0\right) - \mu_n < 0$.

We now examine the log excess returns of the AD Bear portfolio resulting from different types of shocks. Specifically,

$$\Delta P_t = \frac{\partial P_t}{\partial B_t} dB_t + \frac{\partial P_t}{\partial B_{\lambda,t}} dB_{\lambda,t} + \frac{\partial P_t}{\partial J_t} dJ_t$$

First, we solve for the effect of dB_t on P_t. Because dB_t only affects d_n and we have $\frac{\Delta d_n}{dB_t} = -\frac{\phi\sigma}{\nu}$, we have

$$\frac{\partial P_t}{\partial B_t} = \sum_{n=0}^{\infty} \frac{e^{-\lambda_t(T-t)} \left(\lambda_t \left(T-t\right)\right)^n}{n!} N^{'}\left(d_n\right) \times \left(-\frac{\phi\sigma}{\nu}\right)$$
$$= e^{-\lambda_t(T-t)} \left(\sum_{n=0}^{\infty} \delta_n\right) \times \left(-\frac{\phi\sigma}{\nu}\right) \quad \text{(A.13)}$$

where[26]

$$\delta_n = \frac{\left(\lambda_t \left(T-t\right)\right)^n}{n!} \frac{1}{\sqrt{2\pi}} exp\left\{-\frac{1}{2}\left[\frac{log\left(K\right) + b_\phi\lambda_0 + \phi log\left(C_0\right) - \mu_n}{\nu}\right]^2\right\}. \quad \text{(A.14)}$$

Next , the first-order effect of Z_t on P_t is

$$\frac{\partial P_t}{\partial J_t} = e^{-\lambda_t(T-t)} \left(\sum_{n=0}^{\infty} \delta_n\right) \times -\frac{\phi\mu_Z}{\nu} + o\left(Z_t\right) \quad \text{(A.15)}$$

where $o\left(Z_t^2\right)$ is a second and higher order effect.

Finally, we examine the effect of $dB_{\lambda,t}$ on P_t. Letting

$$\frac{\Delta d_n}{dB_{\lambda,t}} = \left[-\frac{b_\phi e^{-\kappa(T-t)}}{\nu} - \frac{\left(log\left(K\right) + b_\phi\lambda_0 + \phi log\left(C_0\right) - \mu_n\right) b_\phi^2 \frac{\sigma_\lambda^2}{2\kappa}\left(1 - e^{-2\kappa T}\right)}{\nu^2}\right] \sigma_\lambda\sqrt{\lambda_t} \quad \text{(A.16)}$$

we have[27]

[26] $\frac{\partial\delta_n}{\partial log(K)} = \delta_n\left[\mu_n - \left(log\left(K\right) + b_\phi\lambda_0 + \phi log\left(C_0\right)\right)\right]$. Because $\mu_n - \left(log\left(K\right) + b_\phi\lambda_0 + \phi log\left(C_0\right)\right) > 0$, $\frac{\partial\delta_n}{\partial log(K)} > 0$.

[27] Note that

$$
\begin{aligned}
\frac{\partial P_t}{\partial B_{\lambda,t}} &= \frac{\partial e^{-\lambda_t(T-t)}\left(\lambda_t\left(T-t\right)\right)^n}{\partial \lambda_t} N\left(d_n\right)\times\sigma_\lambda\sqrt{\lambda_t} + e^{-\lambda_t(T-t)}\left(\sum_{n=0}^{\infty}\delta_n\right)\times\frac{\Delta d_n}{dB_{\lambda,t}} \\
&= e^{-\lambda_t(T-t)}\left(T-t\right)\left[\sum_{n=0}^{\infty}\delta_n\frac{-\phi\mu_Z}{\nu}\right]\times\sigma_\lambda\sqrt{\lambda_t} + e^{-\lambda_t(T-t)}\left(\sum_{n=0}^{\infty}\delta_n\right)\times\frac{\Delta d_n}{dB_{\lambda,t}} \\
&= e^{-\lambda_t(T-t)}\left(\sum_{n=0}^{\infty}\delta_n\right)\times \\
&\quad \left\{\underbrace{\left[-\left(T-t\right)\phi\mu_Z\right]}_{\text{more future jumps}} + \left[\underbrace{-\frac{b_\phi e^{-\kappa T}}{\nu}}_{\text{due to changes in equity price}} \quad \underbrace{-\frac{\eta_n b_\phi^2\frac{\sigma_\lambda^2}{2\kappa}\left(1-e^{-2\kappa T}\right)}{\nu^2}}_{\text{due to changes in equity vol}}\right]\right\}\times \\
&\quad \sigma_\lambda\sqrt{\lambda_t}. \qquad \text{(A.17)}
\end{aligned}
$$

$$
\begin{aligned}
& \frac{\partial\left(e^{-\lambda_t(T-t)}\left(\lambda_t\left(T-t\right)\right)^n\right)}{\partial\lambda_t} \\
=& \frac{\partial\left[e^{-\lambda_t(T-t)+nlog(\lambda_t(T-t))}\right]}{\partial\lambda_t} \\
=& e^{-\lambda_t(T-t)+nlog(\lambda_t(T-t))}\times\left[-\left(T-t\right)+\frac{n}{\lambda_t}\right] \\
=& e^{-\lambda_t(T-t)}\left(\lambda_t\left(T-t\right)\right)^n\times\left[-\left(T-t\right)+\frac{n}{\lambda_t}\right] \\
& \frac{\partial\sum_{n=0}^{\infty}\left(\frac{e^{-\lambda_t(T-t)}\left(\lambda_t(T-t)\right)^n}{n!}\right)}{\partial\lambda_t}N\left(d_n\right) \\
=& \sum_{n=0}^{\infty}\left(\frac{e^{-\lambda_t(T-t)}\left(\lambda_t\left(T-t\right)\right)^n}{n!}\left(-\left(T-t\right)\right)+\frac{e^{-\lambda_t(T-t)}\left(\lambda_t\left(T-t\right)\right)^{n-1}}{\left(n-1\right)!}\left(T-t\right)\right)N\left(d_n\right) \\
=& e^{-\lambda_t(T-t)}\left(T-t\right)\left[\sum_{n=1}^{\infty}\left(-\frac{\left(\lambda_t\left(T-t\right)\right)^n}{n!}+\frac{\left(\lambda_t\left(T-t\right)\right)^{n-1}}{\left(n-1\right)!}\right)N\left(d_n\right)-N\left(d_0\right)\right] \\
=& e^{-\lambda_t(T-t)}\left(T-t\right)\left[\sum_{n=1}^{\infty}\frac{\left(\lambda_t\left(T-t\right)\right)^{n-1}}{\left(n-1\right)!}\left[N\left(d_n\right)-N\left(d_{n-1}\right)\right]\right] \\
=& e^{-\lambda_t(T-t)}\left(T-t\right)\left[\sum_{n=1}^{\infty}\frac{\left(\lambda_t\left(T-t\right)\right)^{n-1}}{\left(n-1\right)!}N'\left(d_{n-1}\right)\frac{-\phi\mu_Z}{\nu}\right] \\
=& e^{-\lambda_t(T-t)}\left(T-t\right)\left[\sum_{n=0}^{\infty}\frac{\left(\lambda_t\left(T-t\right)\right)^n}{n!}N'\left(d_n\right)\frac{-\phi\mu_Z}{\nu}\right].
\end{aligned}
$$

Appendix B Bayes Shrinkage Method

To calculate bear beta, we run rolling-window ordinary least squares (OLS) regressions for each stock to estimate sensitivities to MKT and AD Bear excess returns and adjust these estimates using a Bayes shrinkage method. This appendix presents the derivation of our measure and discusses its implementation.

We develop our measure by considering the following regression model:

$$R_{i,d} = \beta_i^{\text{MKT}} \text{MKT}_d + \beta_i^{\text{BEAR}} R_{\text{AD Bear},d} + \epsilon_{i,d} \tag{B.1}$$

where $R_{i,d}$ is the demeaned return of stock i for time d, MKT_d is the contemporaneous demeaned market excess return, and $R_{\text{AD Bear},d}$ is the contemporaneous demeaned AD Bear excess return. We consider demeaned returns because doing so alleviates the need to include an intercept term in the regression specification, thereby simplifying the derivation. We let $\beta_i = \begin{bmatrix} \beta_i^{\text{MKT}} & \beta_i^{\text{BEAR}} \end{bmatrix}'$ be the vector of true parameter values and $\hat{\beta}_i = \begin{bmatrix} \hat{\beta}_i^{\text{MKT}} & \hat{\beta}_i^{\text{BEAR}} \end{bmatrix}'$ be slope coefficients generated by running an OLS regression specified by equation (B.1).

We follow Fama and French (1997) and take the prior distribution of β_i to be multivariate normal (MVN) with mean vector β and covariance matrix Σ. We also assume that $\epsilon_{i,d}$ follows a normal distribution with mean zero and variance σ_i^2. The posterior distribution of β_i is then multivariate normal with mean $\widetilde{\beta}_i$ given by

$$\begin{aligned} \widetilde{\beta}_i &= \beta + \left(\Sigma^{-1} + \frac{X'X}{\sigma_i^2}\right)^{-1} \frac{X'X}{\sigma_i^2} \left(\hat{\beta}_i - \beta\right) \\ &= \left(\Sigma^{-1} + \frac{X'X}{\sigma_i^2}\right)^{-1} \Sigma^{-1}\beta + \left(\Sigma^{-1} + \frac{X'X}{\sigma_i^2}\right)^{-1} \frac{X'X}{\sigma_i^2} \hat{\beta}_i \end{aligned} \tag{B.2}$$

where X is the matrix of demeaned explanatory returns. Intuitively, $\widetilde{\beta}_i$ shrinks the OLS estimate $\hat{\beta}_i$ toward the prior mean β to correct for the sampling errors. Higher (lower) OLS sampling errors, captured by $\frac{X'X}{\sigma_i^2}$, result in more (less) weight being placed on the prior mean β and less (more) weight being placed on the OLS estimate $\hat{\beta}_i$.

Using the methodology described above, we calculate a value of bear beta for each stock i at the end of each month t as follows. At the end of each month t, we begin by running a standard OLS regression of five-day AD Bear excess returns ($R_{\text{AD Bear}}$) on contemporaneous five-day market portfolio excess returns (MKT) using data from all five trading day periods ending on days d in months $t-11$ through t, inclusive. The regression specification is

$$R_{\text{AD Bear},d} = \delta_0 + \delta_1 \text{MKT}_d + \zeta_d. \tag{B.3}$$

The regression residuals, ζ_d, capture the component of the AD Bear excess return that is orthogonal to the market return. As discussed in our theoretical development of the AD Bear portfolio, ζ_d captures bear market risk.

For each stock i, we then regress the five-day excess stock returns on the contemporaneous market portfolio excess returns and ζ_d using data from the same period that is used estimate regression (B.3). To calculate the five-day stock return $R_{i,d}$, we require that a return for each of the five days be available. We demean the market return within the regression period to eliminate the intercept coefficient from the regression. The regression specification is

$$R_{i,d} = \beta_{i,t}^{\text{m}} \text{MKT}_d + \beta_{i,t}^{\text{BEAR}} \zeta_d + \epsilon_{i,d}. \tag{B.4}$$

We denote the vector slope coefficients estimated from the OLS regression (B.1) $\hat{\beta}_{i,t} = \begin{bmatrix} \hat{\beta}_{i,t}^{\text{m}} & \hat{\beta}_{i,t}^{\text{BEAR}} \end{bmatrix}$. The subscript t indicates values generated by the regression run at the end of month t. We require a minimum of 183 observations, or 180 degrees of freedom, to run the regression.

To implement the Bayes shrinkage method, we need values for the mean and covariance matrix of the prior distribution. The mean of the prior distribution used to calculate Bear beta for all stocks i at the end of month t, which we denote $\beta_t = \begin{bmatrix} \beta_t^{\text{m}} & \beta_t^{\text{BEAR}} \end{bmatrix}$ is taken to be the average value of $\hat{\beta}_{i,t}$ over all observations of $\hat{\beta}_{i,t}$ generated in month t and prior to month t. Specifically,

$$\beta_t = \frac{\sum_{i,\tau \leq t} \hat{\beta}_{i,\tau}}{N} \tag{B.5}$$

where N is the number of valid values of $\hat{\beta}_{i,\tau}$ calculated across all stocks i for months $\tau \leq t$. To calculate the covariance matrix of the prior distribution, we make the assumption that $\beta_{i,t}^{\mathrm{m}}$ and $\beta_{i,t}^{\mathrm{BEAR}}$ are uncorrelated. This makes the covariance matrix of the prior distribution diagonal. The covariance matrix of the prior distribution used for all stocks at the end of month t, which we denote Σ_t, is therefore taken to be the matrix with diagonal entries equal to the pooled variances of $\hat{\beta}_{i,t}^{\mathrm{m}}$ and $\hat{\beta}_{i,t}^{\mathrm{BEAR}}$ and off-diagonal entries set to zero:

$$\Sigma_t = \begin{bmatrix} \sigma_{\mathrm{m,t}}^2 & 0 \\ 0 & \sigma_{\mathrm{BEAR},t}^2 \end{bmatrix} \tag{B.6}$$

where

$$\sigma_{\mathrm{m},t}^2 = \frac{\sum_{i,\tau \leq t} \left(\hat{\beta}_{i,\tau}^{\mathrm{m}} - \beta_t^{\mathrm{m}}\right)^2}{N-1} \tag{B.7}$$

and

$$\sigma_{\mathrm{BEAR},t}^2 = \frac{\sum_{i,\tau \leq t} \left(\hat{\beta}_{i,\tau}^{\mathrm{BEAR}} - \beta_t^{\mathrm{BEAR}}\right)^2}{N-1}, \tag{B.8}$$

both of which are calculated across all stocks i for months $\tau \leq t$.

The last remaining component needed to implement the Bayes shrinkage method is an estimate of the covariance matrix of the OLS estimates $\hat{\beta}_{i,t}^{\mathrm{m}}$ and $\hat{\beta}_{i,t}^{\mathrm{BEAR}}$. We estimate this matrix to be the standard OLS estimate generated by regression (B.4). Since MKT_d and ζ_d are orthogonal, this matrix is diagonal and given by

$$\frac{X_t' X_t}{\sigma_{i,t}^2} = \begin{bmatrix} v_{i,\mathrm{m},t}^{-2} & 0 \\ 0 & v_{i,\mathrm{BEAR},t}^{-2} \end{bmatrix} \tag{B.9}$$

where X_t is the matrix of values of MKT_d and ζ_d used in regression (B.4), and $\sigma_{i,t}^2$ is the variance of the residuals from the regression. v_m^2 and v_{Bear}^2 are therefore the variances of the regression coefficients $\hat{\beta}_{i,t}^{\mathrm{m}}$ and $\hat{\beta}_{i,t}^{\mathrm{BEAR}}$ from regression (B.4), respectively, under the OLS assumptions.

The mean of the posterior distribution, $\widetilde{\beta_{i,t}}$, is then very easy to compute:

$$\widetilde{\beta_{i,t}} = \left(\begin{bmatrix} \sigma_{\mathrm{m},t}^{-2} & 0 \\ 0 & \sigma_{\mathrm{BEAR},t}^{-2} \end{bmatrix} + \begin{bmatrix} v_{\mathrm{m},t}^{-2} & 0 \\ 0 & v_{\mathrm{BEAR},t}^{-2} \end{bmatrix} \right)^{-1} \begin{bmatrix} \sigma_{\mathrm{m},t}^{-2} & 0 \\ 0 & \sigma_{\mathrm{BEAR},t}^{-2} \end{bmatrix} \beta_t$$

$$+ \left(\begin{bmatrix} \sigma_{\mathrm{m},t}^{-2} & 0 \\ 0 & \sigma_{\mathrm{BEAR},t}^{-2} \end{bmatrix} + \begin{bmatrix} v_{\mathrm{m},t}^{-2} & 0 \\ 0 & v_{\mathrm{BEAR},t}^{-2} \end{bmatrix} \right)^{-1} \begin{bmatrix} v_{\mathrm{m},t}^{-2} & 0 \\ 0 & v_{\mathrm{BEAR},t}^{-2} \end{bmatrix} \hat{\beta}_{i,t}$$

$$= \begin{bmatrix} \frac{\sigma_{\mathrm{m},t}^{-2}}{\sigma_{\mathrm{m},t}^{-2}+v_{\mathrm{m},t}^{-2}} & 0 \\ 0 & \frac{\sigma_{\mathrm{BEAR},t}^{-2}}{\sigma_{\mathrm{BEAR},t}^{-2}+v_{\mathrm{BEAR},t}^{-2}} \end{bmatrix} \beta + \begin{bmatrix} \frac{v_{\mathrm{m},t}^{-2}}{\sigma_{\mathrm{m},t}^{-2}+v_{\mathrm{m},t}^{-2}} & 0 \\ 0 & \frac{v_{\mathrm{BEAR},t}^{-2}}{\sigma_{\mathrm{BEAR},t}^{-2}+v_{\mathrm{BEAR},t}^{-2}} \end{bmatrix} \hat{\beta}_{i,t} \qquad \text{(B.10)}$$

The final Bayes shrinkage method value of bear beta used in our empirical analyses is:[28]

$$\beta_{i,t,\mathrm{Bayes}}^{\mathrm{BEAR}} = \frac{\sigma_{\mathrm{BEAR},t}^{-2}}{\sigma_{\mathrm{BEAR},t}^{-2} + v_{\mathrm{BEAR},t}^{-2}} \beta_t^{\mathrm{BEAR}} + \frac{v_{\mathrm{BEAR},t}^{-2}}{\sigma_{\mathrm{BEAR},t}^{-2} + v_{\mathrm{BEAR},t}^{-2}} \hat{\beta}_{i,t}^{\mathrm{BEAR}}. \qquad \text{(B.11)}$$

[28]For brevity, we omit the subscripts $i, t, Bayes$ in the main paper.

References

Agarwal, V., Arisoy, E., and Naik, N. 2016. Volatility of aggregate volatility and hedge fund returns. Journal of Financial Economics, forthcoming.

Agarwal, V. and Naik, N. Y. 2004. Risks and portfolio decisions involving hedge funds. Review of Financial studies, 17(1), 63–98.

Amihud, Y. 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets, 5(1), 31–56.

An, B.-J., Ang, A., Bali, T. G., and Cakici, N. 2014. The joint cross section of stocks and options. Journal of Finance, 69(5), 2279–2337.

Ang, A., Chen, J., and Xing, Y. 2006. Downside risk. Review of Financial Studies, 19(4), 1191–1239.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. 2006. The cross-section of volatility and expected returns. Journal of Finance, 61(1), 259–299.

Arrow, K. J. 1964. The role of securities in the optimal allocation of risk-bearing. The Review of Economic Studies, 31(2), 91–96.

Bali, T. G., Brown, S. J., Murray, S., and Tang, Y. 2016. A lottery demand-based explanation of the beta anomaly. Working Paper.

Bali, T. G., Cakici, N., and Whitelaw, R. F. 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics, 99(2), 427–446.

Bali, T. G., Cakici, N., and Whitelaw, R. F. 2014. Hybrid tail risk and expected stock returns: When does the tail wag the dog? Review of Asset Pricing Studies, pages 207–246.

Bali, T. G. and Hovakimian, A. 2009. Volatility spreads and expected stock returns. Management Science, 55(11), 1797–1812.

Bali, T. G. and Murray, S. 2013. Does risk-neutral skewness predict the cross-section of equity option portfolio returns? Journal of Financial and Quantitative Analysis, 48(4), 1145–1171.

Banz, R. W. 1981. The relationship between return and market value of common stocks. Journal of Financial Economics, 9(1), 3–18.

Barberis, N., Huang, M., and Santos, T. 2001. Prospect theory and asset prices. Quarterly Journal of Economics, 116(1), 1–54.

Basu, S. 1983. The relationship between earnings' yield, market value and return for nyse common stocks: Further evidence. Journal of financial economics, 12(1), 129–156.

Bawa, V. S. and Lindenberg, E. B. 1977. Capital market equilibrium in a mean-lower partial moment framework. Journal of Financial Economics, 5(2), 189–200.

Bondarenko, O. 2014. Why are put options so expensive? The Quarterly Journal of Finance, 4(03), 1450015.

Breeden, D. T. and Litzenberger, R. H. 1978. Prices of state-contingent claims implicit in option prices. Journal of Business, 51(4), 621–651.

Broadie, M., Chernov, M., and Johannes, M. 2009. Understanding index option returns. Review of Financial Studies, 22(11), 4493–4529.

Carhart, M. M. 1997. On persistence in mutual fund performance. Journal of Finance, 52(1), 57–82.

Chabi-Yo, F., Ruenzi, S., and Weigert, F. 2015. Crash sensitivity and the cross-section of expected stock returns. SSRN eLibrary.

Chang, B. Y., Christoffersen, P., and Jacobs, K. 2013. Market skewness risk and the cross section of stock returns. Journal of Financial Economics, 107(1), 46–68.

Coval, J. D. and Shumway, T. 2001. Expected option returns. Journal of Finance, 56(3), 983–1009.

Cremers, M., Halling, M., and Weinbaum, D. 2015. Aggregate jump and volatility risk in the cross-section of stock returns. The Journal of Finance, 70(2), 577–614.

Cremers, M. and Weinbaum, D. 2010. Deviations from put-call parity and stock return predictability. Journal of Financial Quantitative Analysis, 45(2), 335–367.

Debreu, G. *Theory of value: An axiomatic analysis of economic equilibrium.* 17. Yale University Press, 1959.

Dimson, E. 1979. Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics, 7(2), 197–226.

Fama, E. F. and French, K. R. 1992. The cross-section of expected stock returns. Journal of Finance, 47(2), 427–465.

Fama, E. F. and French, K. R. 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56.

Fama, E. F. and French, K. R. 1997. Industry costs of equity. Journal of Financial Economics, 43, 153–193.

Fama, E. F. and French, K. R. 2015. A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1–22.

Fama, E. F. and MacBeth, J. D. 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy, 81(3), 607–636.

Gabaix, X. 2012. Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance. The Quarterly Journal of Economics, 127, 645–700.

Gul, F. 1991. A theory of disappointment aversion. Econometrica, pages 667–686.

Harvey, C. R. and Siddique, A. 2000. Conditional skewness in asset pricing tests. Journal of Finance, 55(3), 1263–1295.

Hou, K., Xue, C., and Zhang, L. 2015. Digesting anomalies: An investment approach. Review of Financial Studies, 28(3), 650–705.

Jackwerth, J. C. 2000. Recovering risk aversion from option prices and realized returns. Review of Financial Studies, 13(2), 433–451.

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. Journal of Finance, 45(3), 881–898.

Jegadeesh, N. and Titman, S. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance, 48(1), 65–91.

Jurek, J. W. and Stafford, E. 2015. The cost of capital for alternative investments. The Journal of Finance, 70(5), 2185–2226.

Kahneman, D. and Tversky, A. 1979. Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–292.

Kelly, B. and Jiang, H. 2014. Tail risk and asset prices. Review of Financial Studies, 27(10), 2841–2871.

Lettau, M., Maggiori, M., and Weber, M. 2014. Conditional risk premia in currency markets and other asset classes. Journal of Financial Economics, 114(2), 197–225.

Lo, A. W. 2001. Risk management for hedge funds: Introduction and overview. Financial Analysts Journal, 57(6).

Markowitz, H. *Portfolio Selection: Efficient Diversification of Investments.* John Wiley and Sons, Inc., New York, New York, 1959.

Merton, R. C. 1976. Option pricing when underlying stock returns are discontinuous. Journal of financial economics, 3(1-2), 125–144.

Mitchell, M. and Pulvino, T. 2001. Characteristics of risk and return in risk arbitrage. Journal of Finance, 56(6), 2135–2175.

Newey, W. K. and West, K. D. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703–708.

Routledge, B. R. and Zin, S. E. 2010. Generalized disappointment aversion and asset prices. The Journal of Finance, 65(4), 1303–1332.

Roy, A. D. 1952. Safety first and the holding of assets. Econometrica, 20, 431–449.

Scholes, M. and Williams, J. T. 1977. Estimating betas from nonsynchronous data. Journal of Financial Economics, 5(3), 309–327.

Seo, S. B. and Wachter, J. A. 2015. Option prices in a model with stochastic disaster risk. Working Paper.

Shleifer, A. and Vishny, R. W. 1997. The limits of arbitrage. The Journal of Finance, 52(1), 35–55.

Shumway, T. 1997. The delisting bias in CRSP data. Journal of Finance, 52(1), 327–340.

Wachter, J. A. 2013. Can time-varying risk of rare disasters explain aggregate stock market volatility? The Journal of Finance, 68(3), 987–1035.

Xing, Y., Zhang, X., and Zhao, R. 2010. What does the individual option volatility smirk tell us about future equity returns? Journal of Financial Quantitative Analysis, 45(3), 641–662.

Figure 1: Construction of AD Bear

The figure below illustrates the construction of the AD Bear portfolio. The full 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.

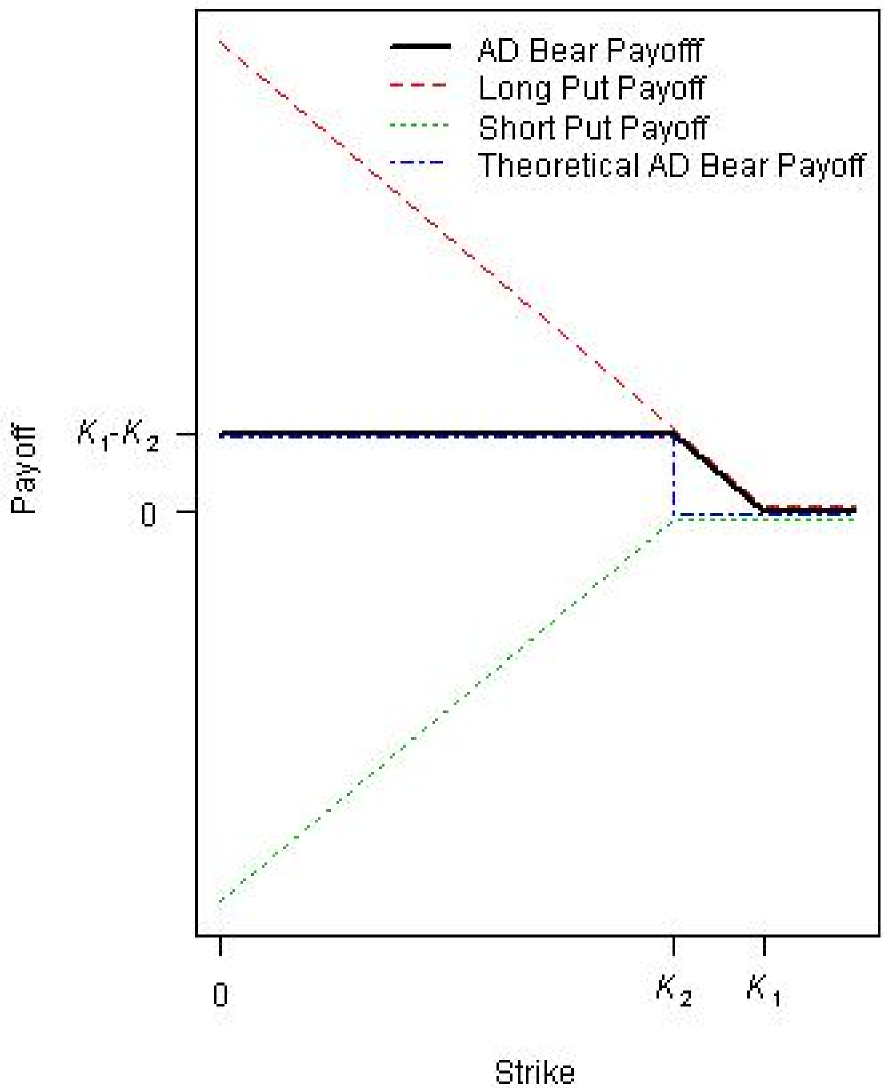

Figure 2: AD Bear CAPM Residuals
The figure below shows the residuals from a regression of AD Bear excess returns on market excess returns (MKT). The numbers 1 - 5 indicate the five largest residuals, in decreasing order.

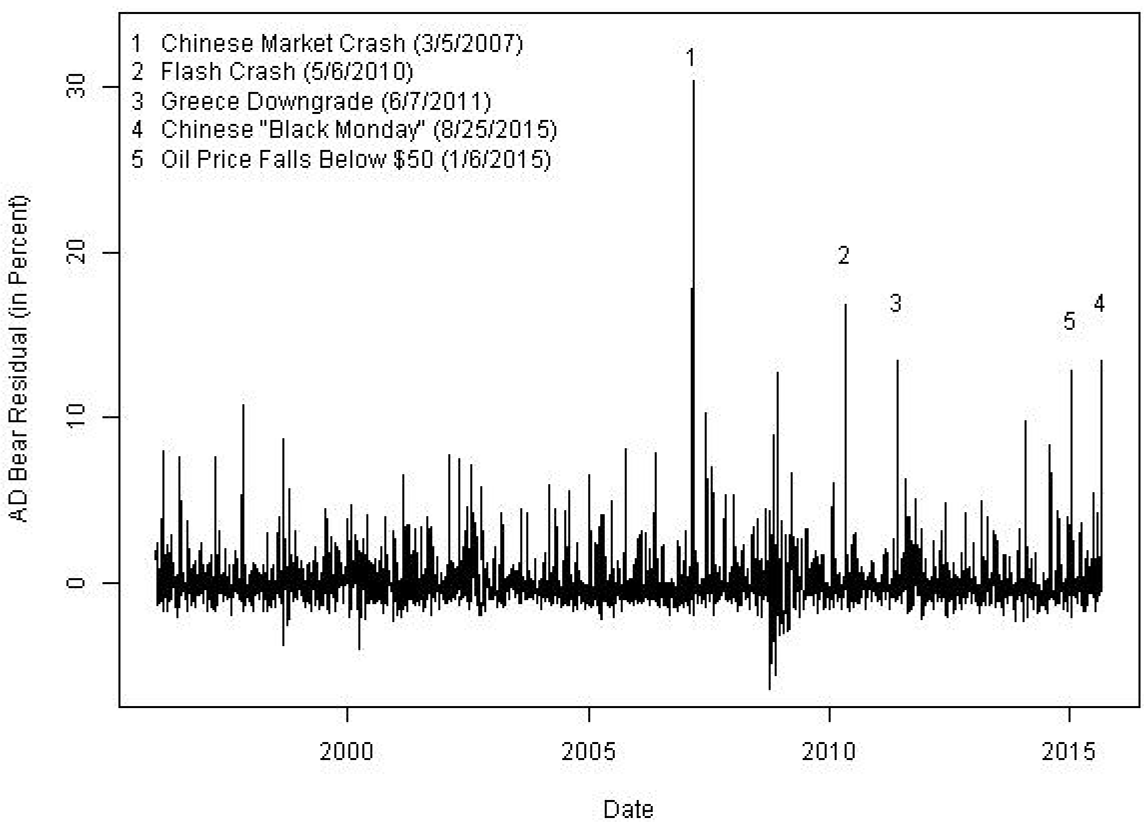

Table 1: Sensitivities of Market Portfolio and AD Bear Returns to Three Sources of Fundamental Risk

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 Wachter's (2013) model 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.. ϕ is the market portfolio's leverage with respect to aggregate consumption, γ is the risk aversion parameter, and $b_{F,\lambda}$ and $b_{\pi,\lambda}$ are the sensitivities of the market return and the stochastic discount factor to $dB_{\lambda,t}$, respectively. $\Delta = e^{-\lambda_t \tau} \left(\sum_{n=0}^{\infty} \delta_n\right) \nu^{-1}$ and τ is time to expiration. Refer to equations (1) to (2) for more parameter definitions. Hedged AD Bear Return is the return to a portfolio that invests in one unit of the AD Bear portfolio and hedges the market exposure by investing ΔX_t in the market portfolio where X_t is the price of the AD Bear portfolio.

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
$dB_{\lambda,t}$	$b_{\pi,\lambda}$	$b_{F,\lambda}$	$\left\{ \begin{array}{c} -b_{F,\lambda} e^{-\kappa\tau} \\ -\varphi b_{F,\lambda}^2 \frac{\sigma_\lambda^2}{2\kappa}\left(1 - e^{-2\kappa\tau}\right) \\ -\tau\phi E\left(Z_t\right) \end{array} \right\} \times\Delta$	$\left\{ \begin{array}{c} -b_{F,\lambda} e^{-\kappa\tau} \quad + b_{F,\lambda} \\ -\varphi b_{F,\lambda}^2 \frac{\sigma_\lambda^2}{2\kappa}\left(1 - e^{-2\kappa\tau}\right) \\ -\tau\phi E\left(Z_t\right) \end{array} \right\} \times\Delta$

Table 2: Summary Statistics for AD Bear Portfolio and Factor Returns

The table below presents summary statistics for the five-day excess returns of the AD Bear portfolio and other factors. Each day d the AD Bear portfolio is formed by taking long positions in one-month S&P 500 index put options with strikes corresponding to approximately a one standard deviation loss on the index and short positions in options with strikes corresponding to a loss of approximately 1.50 standard deviations. The AD Bear portfolio is designed to have a payoff at expiration of $1 if the S&P 500 index experiences a very large loss and a payoff of zero if the index realizes a small loss or gain. The AD Bear portfolio is formed daily and held for five days, at which point the excess return is calculated. 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 returns divided by 28.87836. The scaling factor 28.87836 was chosen so that the standard deviation of the scaled AD Bear excess returns is equal to the standard deviation of the MKT factor returns. The contemporaneous five-day MKT, SMB, HML, MOM, SMB_5, RMW, CMA, ME, IA, and ROE returns are calculated by compounding the daily returns of the factors plus the return on the risk-free security over the contemporaneous five-day period and subtracting the contemporaneous five-day compounded return on the risk-free security. MKT, SMB, HML, and MOM are the excess returns of the market portfolio, the size factor, the value factor, and the momentum factor used in the CAPM, Fama and French (1992) three-factor model (FF3), and the Fama and French (1993) and Carhart (1997) four-factor model (FFC). ME, ROE, and IA and are the excess returns of the size factor, the profitability factor, and the investment factor that, along with the MKT factor, are used in the Hou et al. (2015) Q-factor model (Q). SMB_5, RMW, CMA are the excess returns of the size, profitability, and investment factors that, along with MKT and HML, are used in the Fama and French (2015) five-factor model (FF5). The table presents the mean (Mean), standard deviation (SD), skewness (Skew), minimum value (Min), median value (Median), 95th percentile value (95%), 99th percentile value (99%), and maximum value (Max) 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	SD	Skew	Min	Median	95%	99%	Max
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
IA	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

Table 3: Factor Analysis of AD Bear Portfolio Returns
The table below presents the results of factor regressions of AD Bear portfolio excess returns on the returns of other factors. The row labeled "Excess Return or α" indicates the estimated intercept coefficient. The table shows the intercept coefficient (Excess Return or α), slope coefficients (β_{F}, $\mathrm{F} \in \{\mathrm{MKT}, \mathrm{SMB}, \mathrm{HML}, \mathrm{MOM}, \mathrm{ME}, \mathrm{ROE}, \mathrm{IA}, \mathrm{SM}B_5, \mathrm{RMW}, \mathrm{CMA}\}$), t-statistics, adjusted following Newey and West (1987) using 22 lags, testing the null hypothesis of a zero intercept or slope coefficient (in parentheses), adjusted R-squared (Adj. R^2), and number of observations (n) for each regression.

Value	Excess Return	CAPM	FF3	FFC	Q	FF5
Excess Return or α	−0.28	−0.15	−0.16	−0.14	−0.13	−0.13
	(−3.60)	(−3.83)	(−3.85)	(−3.23)	(−3.09)	(−2.97)
β_{MKT}		−0.81	−0.81	−0.85	−0.85	−0.87
		(−18.58)	(−18.18)	(−20.31)	(−18.07)	(−19.30)
β_{SMB}			0.06	0.07		
			(1.89)	(2.15)		
β_{HML}			0.05	−0.00		0.16
			(1.00)	(−0.09)		(2.86)
β_{MOM}				−0.11		
				(−4.40)		
β_{ME}					0.04	
					(1.20)	
β_{ROE}					−0.14	
					(−2.84)	
β_{IA}					−0.06	
					(−1.18)	
β_{SMB_5}						0.02
						(0.63)
β_{RMW}						−0.16
						(−3.41)
β_{CMA}						−0.25
						(−3.97)
Adj. R^2	0.00%	65.32%	65.47%	66.41%	65.88%	66.39%
n	4910	4910	4910	4910	4910	4910

Table 4: Summary Statistics

The table below presents cross-sectional summary statistics and correlations for variables used in this study. The All Stocks sample holds all U.S.-based stocks in the CRSP 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. Panel A presents the time-series averages of the monthly cross-sectional mean (Mean), standard deviation (SD), skewness (Skew), minimum value (Min), 25th percentile value (25%), median value (Median), 75th percentile value (75%), maximum value (Max), and number of observations with valid values (n) for β^{BEAR}, MKTCAP, and ILLIQ using each sample. Panel B presents the time-series averages of the monthly cross-sectional correlations between β^{BEAR} and each of the other variables. Prior to calculating correlations, each variable is winsorized at the 0.5% and 99.5% levels on a monthly basis. Correlations with β^{JUMP} and β^{VOL} cover the 184 months t from December 1996 through March 2012. Correlations with $\beta^{\Delta\mathrm{SKEW}}$ cover the 133 months t from December 1996 through December 2007. The summary statistics and correlations for all other variables cover the 225 months t from December 1996 through August 2015 (September 2015).

Panel A: Summary Statistics

Sample	Variable	Mean	SD	Skew	Min	25%	Median	75%	Max	n
All Stocks	β^{BEAR}	0.06	0.40	0.23	−1.67	−0.19	0.05	0.30	2.05	4787
	MKTCAP	3176	15163.11	13.66	1	75	308	1335	406290	4784
	ILLIQ	197.52	1081.87	17.41	0.00	0.45	4.75	48.71	36793.82	4502
Liquid	β^{BEAR}	0.08	0.38	0.25	−1.39	−0.16	0.06	0.30	1.69	2041
	MKTCAP	6995	22304.50	9.13	69	743	1600	4368	406290	2041
	ILLIQ	0.69	0.78	1.26	0.00	0.09	0.34	1.06	3.01	2041
Large Cap	β^{BEAR}	0.04	0.34	0.30	−1.16	−0.17	0.02	0.24	1.47	1005
	MKTCAP	13159	30307.80	6.60	1598	2473	4316	10660	406290	1005
	ILLIQ	0.26	1.52	18.78	0.00	0.03	0.08	0.20	42.56	1005

Panel B: Bear Beta Correlations

Sample	β^{CAPM}	β^{-}	$\beta^{\Delta\mathrm{VIX}}$	β^{TAIL}	β^{JUMP}	β^{VOL}	$\beta^{\Delta\mathrm{SKEW}}$	COSKEW	SIZE	BM	MOM	IVOL	ILLIQ
All Stocks	0.19	0.08	0.03	−0.02	0.24	0.15	−0.01	0.05	0.02	−0.06	−0.03	0.03	−0.03
Liquid	0.22	0.11	0.04	0.01	0.27	0.17	−0.00	0.05	−0.11	−0.07	−0.05	0.12	0.05
Large Cap	0.22	0.13	0.05	0.01	0.27	0.17	0.00	0.06	−0.09	−0.09	−0.01	0.13	0.01

Table 5: Fama and MacBeth Regression Analyses

The table below presents the results of Fama and MacBeth (1973) regression analyses of the relation between future stock excess stock returns and β^{BEAR} and control variables. Each month t we run a cross-sectional regression of month $t+1$ excess stock returns on β^{BEAR} and combinations of the 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 three lags, testing the null hypothesis that the average coefficient is equal to zero, are presented in parentheses. The rows labeled Adj. R^2 and n present the average adjusted R-squared value from the regression and number of observations, respectively. Each column presents results for a different regression specification. All independent variables are winsorized at the 0.5% and 99.5% level on a monthly basis. 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 $\beta^{\Delta\text{SKEW}}$ covers the 133 months t (return months $t+1$) from December 1996 (January 1997) through December 2007 (January 2008). 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.

Panel A: All Stocks Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β^{BEAR}	−0.46	−0.36	−0.38	−0.47	−0.51	−0.48	−0.58	−0.51	−0.42	−0.35
	(−2.27)	(−2.06)	(−2.21)	(−2.36)	(−2.21)	(−2.74)	(−2.09)	(−2.66)	(−2.74)	(−3.31)
β^{CAPM}		−0.15							0.00	0.28
		(−0.56)							(0.01)	(1.10)
β^{-}			−0.09						−0.14	−0.13
			(−0.44)						(−0.89)	(−1.03)
$\beta^{\Delta\text{VIX}}$				−0.02					−0.05	−0.03
				(−0.50)					(−1.44)	(−0.88)
β^{JUMP}					0.11					
					(0.23)					
β^{VOL}					0.19					
					(0.89)					
β^{TAIL}						0.16			0.14	0.14
						(1.00)			(0.91)	(1.52)
$\beta^{\Delta\text{SKEW}}$							−0.00			
							(−0.31)			
COSKEW								−0.01	−0.00	0.00
								(−1.16)	(−0.58)	(0.28)
SIZE										−0.18
										(−2.62)
BM										0.04
										(0.44)
MOM										0.00
										(0.59)
IVOL										−0.23
										(−4.68)
ILLIQ										0.00
										(5.29)
Intercept	0.85	0.97	0.94	0.85	0.83	0.87	0.88	0.91	1.00	2.11
	(1.77)	(2.22)	(2.30)	(1.77)	(1.45)	(1.94)	(1.57)	(1.93)	(2.51)	(3.84)
Adj. R^2	0.58%	2.22%	1.85%	0.73%	1.01%	0.94%	0.95%	0.72%	3.00%	5.46%
n	4775	4775	4775	4774	5049	4074	5463	4363	4065	3292

Table 5: Fama and MacBeth Regression Analyses - continued

Panel B: Liquid Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β^{BEAR}	−0.68	−0.50	−0.51	−0.66	−0.64	−0.60	−0.89	−0.68	−0.44	−0.36
	(−2.54)	(−2.82)	(−2.55)	(−2.54)	(−2.30)	(−2.56)	(−2.42)	(−2.62)	(−2.73)	(−2.66)
β^{CAPM}		0.06							0.21	0.14
		(0.14)							(0.54)	(0.42)
β^{-}			0.01						−0.17	−0.21
			(0.04)						(−0.68)	(−1.07)
$\beta^{\Delta\text{VIX}}$				−0.13					−0.12	−0.08
				(−1.60)					(−1.75)	(−1.45)
β^{JUMP}					0.06					
					(0.07)					
β^{VOL}					−0.13					
					(−0.46)					
β^{TAIL}						0.13			0.11	0.14
						(0.75)			(0.80)	(1.33)
$\beta^{\Delta\text{SKEW}}$							0.00			
							(0.26)			
COSKEW								0.00	0.00	0.01
								(0.01)	(0.04)	(0.66)
SIZE										−0.12
										(−1.84)
BM										−0.03
										(−0.40)
MOM										0.00
										(0.40)
IVOL										−0.14
										(−2.49)
ILLIQ										0.24
										(0.83)
Intercept	0.72	0.71	0.74	0.75	0.67	0.74	0.67	0.78	0.80	1.75
	(1.73)	(2.29)	(2.96)	(1.80)	(1.37)	(1.88)	(1.35)	(1.90)	(2.95)	(2.66)
Adj. R^2	1.35%	4.94%	4.20%	1.87%	2.71%	1.89%	2.23%	1.68%	6.39%	9.24%
n	2039	2039	2039	2039	2106	1823	2236	1917	1823	1589

Table 5: Fama and MacBeth Regression Analyses - continued

Panel C: Large Cap Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β^{BEAR}	−0.83	−0.64	−0.60	−0.79	−0.78	−0.73	−1.09	−0.83	−0.53	−0.52
	(−2.71)	(−2.83)	(−2.46)	(−2.71)	(−2.59)	(−2.53)	(−2.50)	(−2.77)	(−2.48)	(−2.63)
β^{CAPM}		0.10							0.27	0.27
		(0.24)							(0.67)	(0.73)
β^{-}			−0.00						−0.19	−0.35
			(−0.01)						(−0.67)	(−1.39)
$\beta^{\Delta\text{VIX}}$				−0.09					−0.07	−0.08
				(−0.80)					(−0.72)	(−0.86)
β^{JUMP}					−1.28					
					(−1.13)					
β^{VOL}					0.13					
					(0.33)					
β^{TAIL}						0.09			0.09	0.15
						(0.46)			(0.63)	(1.25)
$\beta^{\Delta\text{SKEW}}$							0.00			
							(0.12)			
COSKEW								−0.00	−0.01	−0.01
								(−0.30)	(−0.75)	(−0.57)
SIZE										−0.13
										(−2.29)
BM										−0.00
										(−0.04)
MOM										0.00
										(0.78)
IVOL										−0.07
										(−1.21)
ILLIQ										−0.03
										(−0.39)
Intercept	0.68	0.63	0.71	0.69	0.59	0.70	0.61	0.71	0.68	1.80
	(1.84)	(2.24)	(3.15)	(1.87)	(1.36)	(1.95)	(1.50)	(1.96)	(2.69)	(3.28)
Adj. R^2	2.11%	7.14%	6.22%	2.89%	4.40%	2.74%	3.64%	2.49%	9.04%	12.44%
n	1005	1005	1005	1005	1022	932	1073	963	932	794

Table 6: Fama and MacBeth Regression Analyses - k-Month-Ahead Returns

The table below presents the results of Fama and MacBeth (1973) regression analyses of the relation between future stock 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 $k \in 1,2,3,4,5,6$. 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 three 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)-(10) correspond to the specifications used in the corresponding columns of Table 5. 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 $\beta^{\Delta\mathrm{SKEW}}$ covers the 133 months t from December 1996 through December 2007. 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.

Panel A: All Stocks Sample

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R_{t+1}	−0.46	−0.36	−0.38	−0.47	−0.51	−0.48	−0.58	−0.51	−0.42	−0.35
	(−2.27)	(−2.06)	(−2.21)	(−2.36)	(−2.21)	(−2.74)	(−2.09)	(−2.66)	(−2.74)	(−3.31)
R_{t+2}	−0.55	−0.48	−0.49	−0.56	−0.69	−0.58	−0.63	−0.64	−0.56	−0.41
	(−2.90)	(−3.01)	(−3.03)	(−2.93)	(−2.99)	(−3.55)	(−2.52)	(−3.56)	(−3.91)	(−4.06)
R_{t+3}	−0.59	−0.53	−0.53	−0.58	−0.73	−0.65	−0.75	−0.69	−0.63	−0.49
	(−3.18)	(−3.59)	(−3.61)	(−3.14)	(−3.30)	(−4.09)	(−3.09)	(−4.00)	(−4.61)	(−4.60)
R_{t+4}	−0.63	−0.55	−0.57	−0.62	−0.71	−0.69	−0.71	−0.71	−0.64	−0.44
	(−3.35)	(−3.70)	(−3.77)	(−3.31)	(−3.16)	(−4.14)	(−3.03)	(−4.07)	(−4.36)	(−3.79)
R_{t+5}	−0.60	−0.53	−0.54	−0.60	−0.64	−0.65	−0.63	−0.67	−0.63	−0.45
	(−2.95)	(−3.08)	(−3.15)	(−2.94)	(−2.62)	(−3.47)	(−2.46)	(−3.45)	(−3.67)	(−3.45)
R_{t+6}	−0.59	−0.53	−0.54	−0.59	−0.65	−0.59	−0.75	−0.64	−0.59	−0.40
	(−2.86)	(−2.95)	(−3.00)	(−2.89)	(−2.60)	(−3.11)	(−2.93)	(−3.34)	(−3.53)	(−3.27)

Panel B: Liquid Sample

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R_{t+1}	−0.68	−0.50	−0.51	−0.66	−0.64	−0.60	−0.89	−0.68	−0.44	−0.36
	(−2.54)	(−2.82)	(−2.55)	(−2.54)	(−2.30)	(−2.56)	(−2.42)	(−2.62)	(−2.73)	(−2.66)
R_{t+2}	−0.76	−0.58	−0.59	−0.75	−0.82	−0.69	−0.89	−0.78	−0.60	−0.47
	(−2.85)	(−3.33)	(−2.96)	(−2.80)	(−2.73)	(−2.94)	(−2.55)	(−3.05)	(−3.50)	(−3.42)
R_{t+3}	−0.73	−0.55	−0.60	−0.72	−0.85	−0.66	−1.05	−0.74	−0.57	−0.43
	(−2.76)	(−3.32)	(−3.11)	(−2.77)	(−2.87)	(−2.85)	(−3.05)	(−2.97)	(−3.29)	(−2.92)
R_{t+4}	−0.73	−0.54	−0.61	−0.68	−0.76	−0.66	−0.90	−0.74	−0.51	−0.37
	(−2.72)	(−3.08)	(−3.06)	(−2.61)	(−2.66)	(−2.75)	(−2.83)	(−2.90)	(−2.85)	(−2.46)
R_{t+5}	−0.66	−0.47	−0.54	−0.65	−0.60	−0.58	−0.76	−0.64	−0.45	−0.34
	(−2.46)	(−2.63)	(−2.98)	(−2.49)	(−2.03)	(−2.45)	(−2.38)	(−2.59)	(−2.60)	(−2.36)
R_{t+6}	−0.68	−0.48	−0.54	−0.66	−0.67	−0.53	−0.96	−0.64	−0.44	−0.32
	(−2.51)	(−2.48)	(−2.76)	(−2.56)	(−2.17)	(−2.16)	(−2.94)	(−2.55)	(−2.44)	(−2.11)

Table 6: Fama and MacBeth Regression Analyses - k-Month-Ahead Returns - continued

Panel C: Large Cap Sample

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R_{t+1}	−0.83	−0.64	−0.60	−0.79	−0.78	−0.73	−1.09	−0.83	−0.53	−0.52
	(−2.71)	(−2.83)	(−2.46)	(−2.71)	(−2.59)	(−2.53)	(−2.50)	(−2.77)	(−2.48)	(−2.63)
R_{t+2}	−0.89	−0.72	−0.69	−0.87	−0.95	−0.83	−0.97	−0.90	−0.68	−0.57
	(−3.02)	(−3.43)	(−3.07)	(−2.96)	(−3.01)	(−2.94)	(−2.43)	(−3.08)	(−3.14)	(−3.11)
R_{t+3}	−0.74	−0.60	−0.62	−0.72	−0.87	−0.70	−1.00	−0.73	−0.62	−0.55
	(−2.70)	(−3.39)	(−3.21)	(−2.68)	(−3.03)	(−2.78)	(−2.58)	(−2.81)	(−3.44)	(−3.56)
R_{t+4}	−0.64	−0.48	−0.54	−0.57	−0.65	−0.61	−0.82	−0.60	−0.47	−0.33
	(−2.47)	(−2.80)	(−2.91)	(−2.23)	(−2.40)	(−2.55)	(−2.31)	(−2.37)	(−2.78)	(−2.23)
R_{t+5}	−0.66	−0.51	−0.58	−0.65	−0.62	−0.59	−0.73	−0.61	−0.50	−0.39
	(−2.33)	(−2.82)	(−3.01)	(−2.42)	(−2.15)	(−2.23)	(−2.07)	(−2.27)	(−2.81)	(−2.55)
R_{t+6}	−0.73	−0.56	−0.61	−0.67	−0.74	−0.61	−0.88	−0.65	−0.49	−0.44
	(−2.35)	(−2.59)	(−2.71)	(−2.32)	(−2.31)	(−2.08)	(−2.32)	(−2.21)	(−2.53)	(−2.54)

Table 7: Univariate β^{BEAR}-Sorted Portfolios

The table below presents the results of univariate portfolio analyses using β^{BEAR} as the sort variable. 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 10th deciles of β^{BEAR}. The column labeled β^{BEAR} 10−1 presents results for a portfolio that is long stocks in the 10th β^{BEAR} decile portfolio and short stocks in the first β^{BEAR} decile portfolio. The table shows the average month $t+1$ value-weighted excess return (Excess Return), alphas (α) relative to the CAPM, FF3, FFC, Q, and FF5 factor models, and factor sensitivities relative to the FF5 factors. t-statistics, adjusted following Newey and West (1987) using three lags, testing the null hypothesis that the average excess return, alpha, or factor sensitivity, is equal to zero, are presented in parentheses. The rows labeled Pre-Formation show the value-weighted (VW) and equal-weighted (EW) average values of β^{BEAR} for each of the portfolios. The rows labeled Post-Formation present the slope coefficients on AD Bear ($\beta_{\text{AD BEAR}}$) from regressions of the daily five-day overlapping portfolio excess returns on the contemporaneous MKT and AD Bear portfolio excess returns. t-statistics 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.

Panel A: All Stocks Sample

Model	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
Excess Return	Excess Returns	0.99	0.77	0.68	0.47	0.61	0.42	0.44	0.42	0.27	−0.14	−1.13
		(2.51)	(2.37)	(2.33)	(1.53)	(1.87)	(1.09)	(1.11)	(0.91)	(0.54)	(−0.23)	(−2.67)
CAPM	α	0.47	0.30	0.24	0.01	0.09	−0.11	−0.13	−0.21	−0.46	−1.00	−1.48
		(2.46)	(1.85)	(2.15)	(0.08)	(1.00)	(−0.69)	(−0.82)	(−1.18)	(−2.40)	(−3.51)	(−3.59)
FF3	α	0.39	0.26	0.22	−0.00	0.11	−0.07	−0.08	−0.19	−0.43	−0.94	−1.33
		(2.23)	(1.88)	(2.28)	(−0.03)	(1.13)	(−0.53)	(−0.58)	(−1.21)	(−2.56)	(−3.88)	(−3.92)
FFC	α	0.43	0.29	0.23	0.01	0.12	−0.07	−0.06	−0.15	−0.37	−0.82	−1.25
		(2.21)	(2.03)	(2.24)	(0.11)	(0.99)	(−0.53)	(−0.46)	(−0.84)	(−2.14)	(−3.22)	(−3.38)
Q	α	0.34	0.17	0.22	0.04	0.13	0.03	0.01	−0.03	−0.23	−0.51	−0.84
		(1.70)	(1.24)	(1.82)	(0.26)	(0.94)	(0.22)	(0.08)	(−0.20)	(−1.45)	(−1.92)	(−2.41)
FF5	α	0.25	0.16	0.10	−0.03	0.10	−0.03	0.04	0.00	−0.17	−0.46	−0.71
		(1.34)	(1.23)	(1.02)	(−0.26)	(0.94)	(−0.28)	(0.30)	(0.02)	(−1.20)	(−2.07)	(−2.29)
	β_{MKT}	1.10	1.02	0.94	0.91	1.01	0.96	1.00	1.06	1.19	1.25	0.16
		(19.41)	(19.02)	(26.00)	(17.56)	(28.59)	(24.93)	(28.33)	(20.53)	(21.39)	(15.96)	(1.39)
	β_{SMB_5}	0.02	−0.19	−0.03	−0.00	−0.04	0.05	0.02	0.13	0.24	0.37	0.35
		(0.24)	(−2.35)	(−0.46)	(−0.04)	(−0.85)	(1.13)	(0.29)	(2.11)	(2.72)	(3.00)	(2.00)
	β_{HML}	0.09	0.10	−0.06	0.03	−0.05	−0.12	−0.13	−0.01	0.07	−0.10	−0.19
		(0.86)	(0.90)	(−0.85)	(0.35)	(−0.66)	(−1.93)	(−1.94)	(−0.05)	(0.57)	(−0.59)	(−0.77)
	β_{RMW}	0.10	0.01	0.16	0.05	−0.01	0.01	−0.18	−0.28	−0.25	−0.75	−0.85
		(0.60)	(0.08)	(1.98)	(0.82)	(−0.13)	(0.11)	(−2.13)	(−2.68)	(−1.75)	(−6.05)	(−3.26)
	β_{CMA}	0.39	0.38	0.23	0.03	0.02	−0.16	−0.14	−0.29	−0.61	−0.60	−0.99
		(1.63)	(1.61)	(2.36)	(0.19)	(0.17)	(−1.08)	(−1.01)	(−1.74)	(−3.81)	(−2.75)	(−2.39)
Pre-Formation	VW β^{BEAR}	−0.58	−0.32	−0.19	−0.09	0.00	0.09	0.19	0.30	0.45	0.78	1.35
	EW β^{BEAR}	−0.63	−0.33	−0.19	−0.09	0.00	0.09	0.19	0.30	0.46	0.82	1.45
Post-Formation	$\beta_{\text{AD BEAR}}$	−0.04	−0.02	−0.03	−0.03	0.00	−0.01	0.03	0.10	0.16	0.18	0.21
		(−1.44)	(−0.82)	(−1.41)	(−1.91)	(0.18)	(−0.62)	(1.43)	(2.74)	(3.74)	(3.20)	(2.83)

Table 7: Univariate $\beta^{\mathbf{BEAR}}$-Sorted Portfolios - continued

Panel B: Liquid Sample

Model	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
Excess Return	Excess Returns	0.92	0.81	0.68	0.59	0.60	0.41	0.39	0.44	0.23	−0.16	−1.08
		(2.45)	(2.70)	(2.26)	(2.08)	(1.70)	(1.06)	(0.99)	(0.98)	(0.48)	(−0.24)	(−2.41)
CAPM	α	0.44	0.37	0.23	0.15	0.10	−0.15	−0.19	−0.18	−0.50	−1.04	−1.48
		(2.29)	(2.38)	(1.81)	(1.16)	(0.92)	(−1.06)	(−1.32)	(−0.93)	(−2.39)	(−3.46)	(−3.48)
FF3	α	0.37	0.34	0.21	0.12	0.11	−0.08	−0.14	−0.13	−0.46	−0.95	−1.33
		(2.28)	(2.52)	(1.84)	(1.16)	(0.99)	(−0.65)	(−1.09)	(−0.84)	(−2.62)	(−3.83)	(−4.02)
FFC	α	0.41	0.36	0.19	0.11	0.13	−0.04	−0.12	−0.05	−0.39	−0.81	−1.22
		(2.26)	(2.52)	(1.51)	(0.99)	(0.98)	(−0.26)	(−0.86)	(−0.34)	(−2.15)	(−3.07)	(−3.38)
Q	α	0.32	0.26	0.11	0.05	0.13	0.03	−0.04	0.05	−0.24	−0.52	−0.85
		(1.84)	(1.81)	(0.92)	(0.41)	(0.93)	(0.18)	(−0.34)	(0.29)	(−1.34)	(−1.87)	(−2.49)
FF5	α	0.23	0.22	0.04	0.02	0.11	−0.04	0.01	0.08	−0.23	−0.47	−0.70
		(1.35)	(1.74)	(0.44)	(0.16)	(0.97)	(−0.30)	(0.12)	(0.57)	(−1.44)	(−2.06)	(−2.39)
	β_{MKT}	1.05	0.96	1.01	0.93	0.98	1.03	1.01	1.04	1.21	1.31	0.27
		(18.43)	(22.61)	(22.85)	(41.99)	(25.34)	(25.98)	(31.83)	(18.36)	(20.18)	(16.12)	(2.26)
	β_{SMB_5}	−0.06	−0.17	−0.16	−0.02	−0.05	−0.01	−0.03	0.04	0.22	0.26	0.32
		(−0.70)	(−2.36)	(−2.27)	(−0.26)	(−1.14)	(−0.26)	(−0.64)	(0.64)	(2.34)	(1.82)	(1.72)
	β_{HML}	0.07	0.07	−0.02	0.03	0.05	−0.15	−0.06	−0.01	0.04	−0.07	−0.14
		(0.66)	(0.65)	(−0.16)	(0.40)	(0.75)	(−2.33)	(−1.06)	(−0.11)	(0.26)	(−0.41)	(−0.56)
	β_{RMW}	0.11	0.07	0.20	0.17	0.05	0.05	−0.20	−0.25	−0.23	−0.72	−0.82
		(0.63)	(0.68)	(2.97)	(2.97)	(0.83)	(0.67)	(−2.40)	(−2.08)	(−1.36)	(−5.27)	(−3.10)
	β_{CMA}	0.39	0.33	0.32	0.13	−0.11	−0.24	−0.25	−0.40	−0.58	−0.70	−1.08
		(1.48)	(1.94)	(2.10)	(2.06)	(−0.93)	(−1.61)	(−1.93)	(−1.99)	(−3.53)	(−3.10)	(−2.42)
Pre-Formation	VW β^{BEAR}	−0.51	−0.28	−0.16	−0.07	0.02	0.10	0.19	0.30	0.45	0.76	1.27
	EW β^{BEAR}	−0.55	−0.28	−0.16	−0.07	0.02	0.10	0.20	0.31	0.46	0.79	1.34
Post-Formation	$\beta_{\text{AD BEAR}}$	−0.04	−0.04	−0.05	−0.02	−0.04	−0.01	0.01	0.10	0.16	0.19	0.22
		(−1.22)	(−1.52)	(−2.09)	(−1.24)	(−2.01)	(−0.46)	(0.69)	(2.08)	(3.52)	(3.35)	(2.81)

Panel C: Large Cap Sample

Model	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
Excess Return	Excess Returns	0.81	0.83	0.65	0.61	0.63	0.60	0.39	0.20	0.35	−0.15	−0.95
		(2.31)	(2.70)	(2.37)	(2.01)	(1.99)	(1.79)	(1.03)	(0.49)	(0.74)	(−0.24)	(−2.24)
CAPM	α	0.34	0.39	0.24	0.17	0.18	0.10	−0.17	−0.38	−0.33	−0.99	−1.33
		(2.00)	(2.79)	(1.51)	(1.40)	(1.17)	(1.11)	(−1.12)	(−2.22)	(−1.58)	(−3.27)	(−3.21)
FF3	α	0.29	0.38	0.21	0.16	0.16	0.10	−0.09	−0.32	−0.26	−0.88	−1.17
		(2.05)	(2.86)	(1.73)	(1.39)	(1.24)	(1.08)	(−0.67)	(−2.21)	(−1.54)	(−3.75)	(−3.88)
FFC	α	0.31	0.37	0.18	0.14	0.12	0.08	−0.09	−0.29	−0.22	−0.77	−1.08
		(2.00)	(2.55)	(1.37)	(1.15)	(0.97)	(0.82)	(−0.54)	(−2.02)	(−1.17)	(−3.13)	(−3.37)
Q	α	0.22	0.26	0.08	0.06	0.03	0.08	−0.06	−0.20	−0.05	−0.50	−0.72
		(1.47)	(1.90)	(0.71)	(0.50)	(0.20)	(0.83)	(−0.38)	(−1.25)	(−0.28)	(−1.94)	(−2.41)
FF5	α	0.15	0.25	0.05	0.04	0.03	0.06	−0.05	−0.15	−0.02	−0.40	−0.55
		(1.03)	(1.80)	(0.50)	(0.31)	(0.26)	(0.67)	(−0.33)	(−1.18)	(−0.11)	(−1.94)	(−2.17)
	β_{MKT}	1.02	0.97	0.94	0.95	0.95	0.97	1.03	1.00	1.13	1.26	0.24
		(20.24)	(21.57)	(35.84)	(25.67)	(29.87)	(35.55)	(20.73)	(21.29)	(18.31)	(16.12)	(2.18)
	β_{SMB_5}	−0.11	−0.21	−0.15	−0.16	−0.02	0.04	−0.09	−0.04	0.02	0.10	0.21
		(−1.33)	(−3.32)	(−3.00)	(−3.30)	(−0.35)	(0.84)	(−1.71)	(−0.64)	(0.33)	(0.75)	(1.15)
	β_{HML}	0.08	0.03	0.07	0.05	−0.03	−0.00	−0.14	−0.06	0.00	−0.08	−0.16
		(0.72)	(0.30)	(0.98)	(0.69)	(−0.39)	(−0.07)	(−2.32)	(−0.61)	(0.02)	(−0.48)	(−0.64)
	β_{RMW}	0.13	0.12	0.26	0.16	0.19	0.11	0.01	−0.23	−0.30	−0.73	−0.86
		(0.81)	(1.66)	(3.60)	(2.37)	(2.96)	(2.16)	(0.11)	(−2.02)	(−2.21)	(−5.39)	(−3.34)
	β_{CMA}	0.35	0.31	0.20	0.20	0.19	−0.05	−0.19	−0.25	−0.48	−0.65	−1.00
		(1.49)	(2.64)	(1.81)	(1.98)	(2.56)	(−0.81)	(−1.42)	(−1.31)	(−2.98)	(−3.03)	(−2.41)
Pre-Formation	VW β^{BEAR}	−0.48	−0.27	−0.17	−0.09	−0.01	0.06	0.14	0.24	0.37	0.66	1.14
	EW β^{BEAR}	−0.51	−0.27	−0.17	−0.09	−0.01	0.06	0.14	0.24	0.38	0.68	1.19
Post-Formation	$\beta_{\text{AD BEAR}}$	−0.03	−0.05	−0.06	−0.03	−0.03	−0.05	−0.01	0.02	0.14	0.20	0.22
		(−0.92)	(−2.19)	(−2.61)	(−1.57)	(−1.28)	(−3.68)	(−0.31)	(0.93)	(2.78)	(3.75)	(2.90)

Table 8: Bivariate β^{BEAR}-Sorted Portfolios-Sorted Portfolios for Liquid Sample

The table below presents the results of bivariate portfolio analyses using a control variable and β^{BEAR} as the sort variables. The control variable is one of β^{CAPM}, β^{-}, $\beta^{\Delta\mathrm{VIX}}$, β^{TAIL}, β^{JUMP}, β^{VOL}, $\beta^{\Delta\mathrm{SKEW}}$, COSKEW, MKTCAP, BM, MOM, IVOL, and ILLIQ. 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 100 portfolios, as well as for the zero-investment portfolios that are long the β^{BEAR} decile 10 portfolio and short the β^{BEAR} decile one portfolio in each control variable decile, are calculated (β^{BEAR} $10-1$ portfolio). Within each β^{BEAR} decile, as well as for the β^{BEAR} $10-1$ portfolio, we then calculate the equal-weighted average of the portfolio excess returns across the deciles of the control variable. The table presents the time-series averages of the month $t+1$ excess returns for the average control variable portfolio in each of the β^{BEAR} deciles. 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 CAPM, FF3, FFC, Q, and FF5 factor models, and factor sensitivities relative to the FF5 factors. t-statistics, adjusted following Newey and West (1987) using three lags, testing the null hypothesis that the average excess return, alpha, or factor sensitivity, is equal to zero, are presented in parentheses. The results shown are for the analysis using the Liquid sample. The analyses that control for β^{JUMP} or β^{VOL} cover the cover the 184 months t (return months $t+1$) from December 1996 (January 1997) through March 2012 (April 2012). The analysis that controls for $\beta^{\Delta\mathrm{SKEW}}$ covers the cover the 133 months t (return months $t+1$) from December 1996 (January 1997) through December 2007 (January 2008). All other analyses cover the 225 months t (return months $t+1$) from December 1996 (January 1997) through August 2015 (September 2015).

	Model	Value	β^{CAPM} Avg	β^{-} Avg	$\beta^{\Delta\mathrm{VIX}}$ Avg	β^{TAIL} Avg	β^{JUMP} Avg	β^{VOL} Avg	$\beta^{\Delta\mathrm{SKEW}}$ Avg	COSKEW Avg	MKTCAP Avg	BM Avg	MOM Avg	IVOL Avg	ILLIQ Avg
β^{BEAR} 1	Excess Return	Excess Return	0.77	0.82	0.89	0.98	0.90	0.90	1.03	0.94	0.99	0.92	0.85	0.89	1.04
β^{BEAR} 2			0.64	0.54	0.93	0.89	0.82	0.71	0.88	0.84	1.02	0.85	0.80	0.82	0.94
β^{BEAR} 3			0.64	0.60	0.59	0.57	0.47	0.71	0.55	0.80	0.95	0.71	0.72	0.67	0.84
β^{BEAR} 4			0.61	0.45	0.52	0.69	0.65	0.65	0.53	0.71	0.82	0.47	0.48	0.60	0.86
β^{BEAR} 5			0.57	0.68	0.73	0.64	0.63	0.71	0.79	0.74	0.69	0.66	0.62	0.58	0.69
β^{BEAR} 6			0.54	0.66	0.54	0.64	0.41	0.70	0.75	0.67	0.69	0.41	0.64	0.55	0.73
β^{BEAR} 7			0.48	0.57	0.54	0.65	0.32	0.36	0.41	0.46	0.64	0.50	0.58	0.68	0.61
β^{BEAR} 8			0.44	0.54	0.36	0.57	0.33	0.27	0.28	0.49	0.67	0.49	0.37	0.40	0.59
β^{BEAR} 9			0.47	0.57	0.44	0.39	0.23	0.21	0.11	0.43	0.35	0.52	0.21	0.36	0.37
β^{BEAR} 10			0.10	0.05	−0.17	0.18	−0.12	−0.32	−0.50	−0.04	0.08	0.10	−0.30	0.09	0.10
β^{BEAR} 10-1	Excess Return	Excess Returns	−0.67	−0.77	−1.07	−0.80	−1.02	−1.21	−1.53	−0.98	−0.91	−0.82	−1.15	−0.81	−0.94
			(−3.21)	(−3.25)	(−2.56)	(−2.67)	(−2.24)	(−2.60)	(−2.43)	(−2.73)	(−2.37)	(−2.40)	(−2.76)	(−2.47)	(−2.49)
	CAPM	α	−0.78	−0.94	−1.40	−1.08	−1.27	−1.50	−1.92	−1.31	−1.21	−1.13	−1.43	−1.02	−1.23
			(−3.81)	(−4.07)	(−3.31)	(−3.71)	(−2.78)	(−3.29)	(−3.23)	(−3.94)	(−3.16)	(−3.37)	(−3.31)	(−3.11)	(−3.23)
	FF	α	−0.75	−0.92	−1.28	−1.00	−1.12	−1.40	−1.32	−1.21	−1.07	−1.03	−1.28	−0.95	−1.11
			(−3.92)	(−4.40)	(−4.05)	(−3.98)	(−3.47)	(−3.82)	(−2.99)	(−4.33)	(−3.90)	(−3.84)	(−4.24)	(−3.50)	(−3.85)
	FFC	α	−0.78	−0.91	−1.18	−0.90	−1.14	−1.32	−1.41	−1.10	−0.95	−0.96	−1.27	−0.92	−1.02
			(−3.75)	(−3.90)	(−3.39)	(−3.16)	(−3.36)	(−3.45)	(−2.77)	(−3.44)	(−3.12)	(−3.24)	(−3.85)	(−3.10)	(−3.26)
	Q	α	−0.69	−0.82	−0.84	−0.63	−0.80	−0.93	−1.22	−0.83	−0.51	−0.60	−0.96	−0.70	−0.58
			(−3.10)	(−3.52)	(−2.57)	(−2.35)	(−2.52)	(−2.75)	(−2.34)	(−2.75)	(−1.95)	(−2.06)	(−3.33)	(−2.50)	(−2.10)
	FF5	α	−0.70	−0.81	−0.78	−0.58	−0.65	−0.75	−0.92	−0.79	−0.54	−0.58	−0.83	−0.64	−0.57
			(−3.31)	(−3.95)	(−2.85)	(−2.38)	(−2.17)	(−2.40)	(−2.23)	(−3.06)	(−2.32)	(−2.37)	(−3.64)	(−2.60)	(−2.35)
		β_{MKT}	0.07	0.16	0.22	0.22	0.18	0.23	0.09	0.26	0.13	0.17	0.18	0.16	0.11
			(1.28)	(2.29)	(2.18)	(2.45)	(1.68)	(1.97)	(0.50)	(2.42)	(1.08)	(1.54)	(2.39)	(2.30)	(0.90)
		β_{SMB_5}	0.36	0.40	0.36	0.23	0.38	0.32	0.31	0.35	0.31	0.53	0.16	0.16	0.36
			(3.85)	(3.36)	(2.04)	(1.87)	(2.38)	(1.70)	(1.56)	(2.25)	(1.80)	(3.36)	(1.13)	(1.14)	(1.95)
		β_{HML}	−0.28	−0.13	−0.14	0.03	−0.38	−0.09	−0.52	−0.14	−0.19	−0.18	−0.17	−0.10	−0.22
			(−2.09)	(−0.77)	(−0.64)	(0.13)	(−1.61)	(−0.33)	(−1.85)	(−0.60)	(−0.76)	(−0.72)	(−0.98)	(−0.55)	(−0.79)
		β_{RMW}	−0.09	−0.04	−0.59	−0.42	−0.49	−0.72	−0.44	−0.50	−0.71	−0.44	−0.55	−0.44	−0.72
			(−0.59)	(−0.24)	(−2.11)	(−2.24)	(−1.72)	(−2.55)	(−1.60)	(−2.20)	(−3.32)	(−2.22)	(−2.29)	(−2.02)	(−2.99)
		β_{CMA}	−0.04	−0.37	−1.01	−0.95	−0.78	−1.00	−0.95	−0.80	−0.88	−1.01	−0.85	−0.48	−0.88
			(−0.21)	(−1.19)	(−2.80)	(−2.73)	(−1.91)	(−2.49)	(−1.74)	(−2.20)	(−1.97)	(−2.38)	(−2.89)	(−1.81)	(−1.80)