Bear Beta*

Zhongjin Lu[†] Scott Murray[‡]

This version: March 2017

Abstract

We test whether bear market risk – time-variation in the probability of future bear market states – is priced. Theoretically, short-term returns of an Arrow-Debreu security that pays off in terminal bear market states (AD Bear) capture bear market risk. Empirically, we construct AD Bear using traded S&P 500 index options and find that stocks with high sensitivity to AD Bear returns (stocks that outperform when bear market risk increases) earn average monthly returns 1% lower than stocks with low sensitivity. Consistent with risk-based explanations, the negative relation is persistent, robust, and remains strong among liquid and large stocks.

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

---

*Finalist for 2017 AQR Insight Award (winner to be determined in April 2017). We thank Robert Hodrick for earlier discussions on downside risk that inspired this project. We thank Vikas Agarwal, Andrew Ang, Turan Bali, Pierre Collin-Dufresne, George Gao, Mehdi Haghbaali, Campbell Harvey, John Hund, Kris Jacobs, Dalida Kadyrzhanova, Haim Kassa, Lars Lochstoer, Dmitriy Muravyev, Narayan Naik, Bradley Paye, Neil Pearson, Chip Ryan, Suresh Sundaresan, Jessica Wachter, Yuhang Xing, Baozhang Yang, Xiaoyan Zhang, and seminar participants at the 2017 INQUIRE UK & Europe Joint Conference, 2017 Financial Management Association Latin America Conference, 2016 All Georgia Conference, Georgia State University, the University of Georgia, Arizona State University, PBC School of Finance at Tsinghua University, Fidelity Management and Research, and JP Morgan Investment Management for insightful comments that have substantially improved the paper.

[†]Assistant Professor of Finance, Terry College of Business, University of Georgia, Athens, GA 30602; email zlu15@uga.edu.

[‡]Assistant Professor of Finance, J. Mack Robinson College of Business, Georgia State University, Atlanta, GA 30303; email smurray19@gsu.edu.

1 Introduction

This paper examines the pricing implications of bear market risk. We define bear market risk as time-variation in the ex-ante probability of future bear market states (i.e., states in which the market portfolio suffers a large loss). Bear market risk is distinct from risk driven by realized market losses as studied in Ang, Chen, and Xing (2006): regardless of whether or not the market is currently in a bear market state, changes in the probability of future bear market states impact asset prices. The importance of this distinction is highlighted by Gabaix (2012) and Wachter (2013), who demonstrate theoretically that time-variation in disaster risk, the consumption analog of bear market risk, explains many macroeconomic asset pricing puzzles.

Our key innovation is to develop a measure of bear market risk. Motivated by Breeden and Litzenberger (1978), we construct an Arrow (1964) and Debreu (1959) portfolio – AD Bear – from traded S&P 500 index options. The AD Bear portfolio pays off $1 when the market at expiration is in a bear state.[1] Therefore, the price of the AD Bear portfolio is a forward-looking measure of the (risk-neutral) probability of future bear market states and the short-term AD Bear return reflects the change in this probability, i.e., bear market risk.[2] Using Wachter (2013)'s model, we demonstrate that bear market risk is priced differently than CAPM market risk and show that we can measure exposure to bear market risk by augmenting the CAPM model with AD Bear returns.

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

Our focal tests examine the cross-sectional relation between future stock returns and bear beta (sensitivity to the AD Bear return). We find that the post-formation returns of value-weighted decile portfolios sorted on bear beta exhibit a strong decreasing pattern

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

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

across bear beta deciles. A zero-investment portfolio that goes long the top bear beta decile portfolio and short the bottom decile portfolio generates an average return of about -1% per month, three-factor alpha of about -1.25% per month, and five-factor alpha of about -0.70% per month. This strong and robust negative cross-sectional relation between bear beta and *future* stock returns is particularly striking in light of the well-documented inability of other theoretically motivated factor sensitivity variables, such as CAPM beta, to predict future stock returns.

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 pattern similar to that of the pre-formation sensitivities. The spread in post-formation bear market risk 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 portfolio tests using samples containing only liquid stocks and large cap stocks (approximately the 2000 most liquid stocks and the 1000 largest stocks, respectively), for which arbitrage costs are minimal, and find similar, if not stronger, results. To our knowledge, bear beta is the first sensitivity measure based on a non-stock-return factor that successfully generates significant spreads in both post-formation returns and post-formation factor sensitivities.

We are careful to differentiate the negative cross-sectional relation between bear beta and future returns from previously documented relations between risk and expected returns. We use bivariate portfolio analysis to control for several known risk-based pricing effects. Most importantly, we control for the downside beta in Ang, Chen, and Xing (2006). We also control for measures of aggregate volatility and jump risk such as VIX beta (Ang, Hodrick, Xing, and Zhang (2006)) and the jump and volatility betas used in Cremers et al. (2015). To ensure that our results are not driven by exposure to aggregate skewness risk, we control for coskewness (Harvey and Siddique (2000)) and aggregate skewness beta (Chang et al. (2013)). Finally, we control for tail beta (Kelly and Jiang (2014)) and idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006)). Our results demonstrate that none of these risk measures explains the negative relation between bear beta and expected stock returns. We then use Fama and MacBeth (1973, FM hereafter) regression analyses to simultaneously control for these risk measures, as well as other known determinants of expected returns such as market capitalization and the book-to-market ratio in Fama and French (1992), momentum in Jegadeesh and Titman (1993), illiquidity in Amihud (2002), and profitability and investment in Fama and French (2015). The negative cross-sectional relation between bear beta and expected stock returns is highly robust to controlling for these previously documented effects in all three samples and the predictive power of bear beta persists for at least six months into the future.

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 combine the insights in Ang, Chen, and Xing (2006) and Breeden and Litzenberger (1978) and introduce a forward-looking measure of downside risk. Ang, Chen, and Xing (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 changes in the probability of future bear states, it does not rely on bear state realizations. This offers two advantages. First, even though bear market states occur infrequently, because the probability of future bear market states varies continuously, we are able to use the full set of data to calculate bear beta. Second, bear beta is not subject to the potential peso problem arising from the fact that, in periods of prosperity, even the lowest returns may not represent bear states. These two advantages are shared by the tail beta in Kelly and Jiang (2014). However, tail beta and bear beta are very different measures. Kelly and Jiang (2014) measure tail risk by aggregating large daily losses on individual stocks. Furthermore, tail beta is computed using regressions of excess stock returns on lagged tail risk, whereas bear beta conforms to the traditional definition of risk exposure and measures contemporaneous covariance between excess stock returns and excess AD Bear returns.

[3] Subsequent research follows this general theme. Bali et al. (2014) find that the left tail return covariance between individual stocks predicts future stock returns. Lettau et al. (2014) show that market betas differ depending on the market state and that betas in bad market states are a key determinant of expected returns for many asset classes. Chabi-Yo et al. (2015) find that stocks that underperform during crashes generate higher average returns.

Our paper also adds to the research that uses the forward-looking information in option prices to investigate relations between aggregate risk and the cross section of expected stock returns.[4] Ang, Hodrick, Xing, and Zhang (2006) and Cremers et al. (2015) find that aggregate volatility risk is priced in the cross section of stock returns. Cremers et al. (2015) also find that jump risk is priced. Finally, Chang et al. (2013) investigate whether innovations in the risk-neutral skewness of the market return is a risk factor and find a negative price of risk. Since AD Bear has positive vega and gamma exposures, it is not surprising that bear beta has a positive cross-sectional relation with the VIX beta in Ang, Hodrick, Xing, and Zhang (2006), as well as the volatility beta and jump beta used in Cremers et al. (2015). Intuitively, bear beta is negatively correlated with Chang et al. (2013)'s skewness beta since, all else equal, an increase in bear market risk decreases risk-neutral skewness. However, our work differs from these previous studies in our focus on risk associated with future left-tail market outcomes, whereas volatility, skewness, and jump beta capture exposure to the full spectrum of the market return distribution. Empirically, we find that including jump beta, volatility beta, VIX beta, and skewness beta as controls does not explain the bear beta effect.

The remainder of this paper proceeds as follows. In Section 2 we develop the theoretical motivation for our main research question and for the 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 return is priced in the cross section of stocks. Section 5 demonstrates that our results are robust after controlling for previously documented pricing effects. Section 6 concludes.

2 Theoretical Motivation for AD Bear

We begin by motivating AD Bear returns as a measure of bear market risk using Wachter (2013)'s time-varying rare disaster model.[5] The benefit of doing so is a clear exposition of

[4]Bollerslev and Todorov (2011) use options to empirically demonstrate that time-varying tail risk is an important driver of the equity risk premium. 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 et al. (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 et al. (2010), Bali and Murray (2013), An et al. (2014)).

[5]We choose to develop the economic interpretation of the AD Bear returns using Wachter (2013)'s time-varying disaster model because the AD Bear price is the discounted risk-neutral probability that the market is in a bear state at expiration and Wachter (2013) explicitly models the impact of time-variation in the probability of negative jumps. However, AD Bear returns can be similarly interpreted from the perspectives of other models that feature time-varying bear market risk.

the relation between the pricing kernel, market risk, bear market risk, and AD Bear returns.[6]

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 the probability 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 π_t, F_t, and X_t to the three sources of risk.[7] 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 by controlling for jump risk, coskewness, and aggregate skewness risk.

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 $b_{\pi,\lambda}$ which is greater than zero since an increase in the intensity of jumps increases marginal utility.

We now examine the market portfolio return. An 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

[6] Harvey et al. (2015) and Harvey (2017) emphasize the importance of having a well-motivated hypothesis based on first principles.

[7] All derivations are shown in Appendix A.

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 and, to correctly price assets, one must account for the effect of bear market risk (i.e., innovations in jump intensity).

Most importantly, 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 Δ 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 economic insights from the above discussions are two-fold. First, in the presence of bear market risk (captured in this model by time-variation in jump intensity), the market risk factor is insufficient to price assets, i.e., the CAPM does not hold. Second, the AD Bear portfolio is proportionally more sensitive than the market portfolio to bear market risk. Therefore, we can measure exposure to bear market risk by augmenting the CAPM model with the returns of the AD Bear portfolio.

3 AD Bear Portfolio

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 hereafter).[8] To ensure data quality, we remove options with bid prices of zero and options that violate simple arbitrage conditions, as indicated by a missing implied volatility in OM. We define the price of an option to be the average of the bid and offer prices and the dollar trading volume to be the number of contracts traded times the option price. The S&P 500 index forward price is taken to be $F = S_0 e^{(r-y)T}$ where S_0 is the closing level of the S&P 500 index, r is the continuously compounded risk-free rate, y is the dividend yield of the S&P 500 index, and T is the time to expiration.

[8] 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.

3.2 Construction of AD Bear

Theoretically, the AD Bear portfolio generates a payoff of \$1 when the S&P 500 index level at expiration is in a bear state, defined as index levels below some value K_2, and zero otherwise. To approximate this payoff structure using traded options, we can take a long position in a put option with strike price $K_1 > K_2$ and a short position in a put option with strike price K_2. Scaling both positions by $K_1 - K_2$, as shown in Figure 1, the resulting AD Bear portfolio has a payoff at expiration of \$1 when the index level is below K_2 and zero when the index level is above K_1. The payoff linearly decreases from \$1 to zero for expiration index levels between K_2 and K_1.[9] The price of the AD Bear portfolio, $P_{\text{AD Bear}}$, is therefore

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

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

When implementing the AD Bear portfolio, we make several empirical choices that are largely driven by features of the option data. First, motivated by liquidity considerations, we create the AD Bear portfolio using one-month options, which are defined as options that expire in the calendar month subsequent to the month in which the portfolio is created.[10]

Second, we target a strike of 1.5 standard deviations below the S&P 500 index forward price for K_2. Following Jurek and Stafford (2015), we take the standard deviation to be the level of the VIX index divided by 100 multiplied by the square root of the time to expiration. This is equivalent to defining bear market states to be states in which the market excess return is more than 1.5 standard deviations below zero. We choose 1.5 standard deviations based on a trade off between our objective of capturing the pricing effect of states with very high marginal utility and the practical consideration that very far out-of-the-money (OTM) put options are illiquid, making their pricing unreliable and frequently unavailable in the data.[11]

---

[9] An alternative approach to measuring the price of the AD Bear portfolio would be to estimate the cumulative risk-neutral density evaluated at K_2 by using an interpolation technique to generate a continuum of option prices (see Figlewski (2010)). This alternative approach requires making assumptions about the functional form of the relation between strike prices and option prices. Our approach alleviates the need to make such assumptions and has the added benefit that the AD Bear portfolio is easily constructed from traded options. Carr and Wu (2011) construct portfolios similar to our AD Bear portfolio using single-stock options to replicate credit insurance contracts.

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

[11] Our bear region corresponds to approximately the worst 6.7% of market states under the assumption of log-normally distributed returns.

Third, since it is unlikely that a traded option with the exact targeted strike exists, we take $P(K_2)$ to be the dollar trading volume-weighted average price of all puts with strikes between 0.25 standard deviations below and above the target strike. 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.[12] Specifically, we have:

$$P(K_2) = \sum_{K \in \left[Fe^{-1.75\frac{VIX}{100}\sqrt{T}},Fe^{-1.25\frac{VIX}{100}\sqrt{T}}\right]} P(K)w(K) \tag{4}$$

where the summation is taken over all traded puts with strikes in the indicated range and $w(K)$ is the dollar trading volume of the put with strike K scaled by the total dollar trading volume of all puts in the summation.

Finally, we choose K_1 to be half a standard deviation above K_2 (i.e. one standard deviation below the forward price). Theoretically, the payoff function of our traded option portfolio converges to the theoretical AD Bear payoff function as $K_1 - K_2$ approaches zero. Empirically, as K_1 approaches K_2, the difference between $P(K_2)$ and $P(K_1)$ approaches zero, and the informational content of the price difference can be overwhelmed by bid-ask spread-induced noise. Choosing $K_1 - K_2$ to be half a standard deviation balances these two considerations. We calculate $P(K_1)$ using equation (4) with the summation range adjusted to be from -1.25 to -0.75 standard deviations below zero.

It is worth noting that by defining the bear region to be 1.5 standard deviations below zero, the price of the AD Bear portfolio (i.e., the discounted risk-neutral probability of a bear market outcome) is approximately constant at the time the portfolio is created. Thus, while the AD Bear portfolio returns capture innovations in bear market risk, the price of the AD Bear portfolio at the time of construction does not reflect the level of bear market risk.

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 buy-and hold return on this AD Bear portfolio over the next five-trading days (one calendar week except when there is a holiday). The choice to use a five-day

[12] In Section II and Table A1 of the online appendix, we show that our results are highly robust, and in many cases stronger, if we give each option an equal weight when constructing the AD Bear portfolio.

return is based on a trade-off between theory and practical considerations. Our theoretical motivation is based on instantaneous returns, which leads us to use a return period as short as possible. However, bear betas computed using short-term returns 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.[13] We subtract the five-day risk-free rate from the five-day buy-and-hold AD Bear return to get the AD Bear portfolio excess return for the five day period ending on day d, which we denote $R_{\text{AD Bear},d}$.[14] The result is a time-series of overlapping five-day AD Bear portfolio excess returns for the period from January 11, 1996 through August 31, 2015.[15]

Table 2 presents summary statistics for the daily five-day overlapping excess returns of the AD Bear portfolio. Since AD Bear pays off in high marginal utility states, we expect it to earn negative average excess returns. The first row of the table presents results for the unscaled AD Bear returns. Consistent with our prediction, 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 AD Bear excess returns reflects the leverage embedded in options. To facilitate comparison with other factors, for the remainder of this paper, we scale the AD Bear excess returns by 28.87836 so that the standard deviation of the scaled AD Bear excess returns is equal to that of the market excess returns. The row labeled "AD Bear" presents summary statistics for the scaled AD Bear portfolio excess returns. The AD Bear portfolio generates a scaled average excess return of -0.28% per five-day period with a standard deviation of 2.59. 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).[16] The mean five-day excess returns of the

[13]In untabulated results, we find that the results using four-day AD Bear returns are very similar to, and often stronger than, the results using five-day AD Bear returns. Consistent with the notion that beta measures based on very short returns are noisy due to nonsynchronous trading, the results get weaker as we progress to using three-day, two-day, and one-day AD Bear returns.

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

[15]If insufficient data are available to calculate the AD Bear return (see Jurek and Stafford (2015)), we consider the return for the given five-day period to be missing. There are 4910 valid returns out of 4944 days during the sample period.

[16]MKT, SMB, HML, MOM, SMB_5, RMW, and CMA factor return data are gathered from Kenneth

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

$$R_{\text{AD Bear},d} = \alpha + \beta^{'}\mathbf{F_d} + \epsilon_d. \tag{5}$$

The standard risk factors we use are returns of zero-investment portfolios. The average returns of these portfolios capture the factor risk premia. Therefore, α in regression (5) measures the average return of the AD Bear portfolio that is not compensation for exposure to the risk factors considered. AD Bear has positive exposure to bear market risk and bear market risk is predicted to carry a negative premium. If bear market risk is distinct from previously identified factors, then our hypothesis predicts that AD Bear should generate negative alpha relative to standard factor models.

Before proceeding to the factor model analyses, we first examine whether the average AD Bear excess return is statistically distinguishable from zero. Table 3 shows that the average AD Bear excess return of -0.28% per five-day period is highly significant with a Newey and West (1987, NW hereafter)-adjusted t-statistic of -3.60.

Our first factor analysis in Table 3 examines whether the premium earned by the AD Bear portfolio can be explained by exposure to CAPM market risk. Consistent with the prediction from the model derived in Section 2, despite AD Bear's strong negative exposure to the market factor ($\beta_{\text{MKT}} = -0.81$), the average AD Bear excess return cannot be fully explained by market factor exposure. AD Bear's alpha relative to the CAPM model is -0.15% per five days, highly significant with a t-statistic of -3.83. This is our first indication of a negative price of bear market risk.

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 the risk factor models proposed by Fama and

French's data library. We thank Lu Zhang for providing the 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 gross compounded return of the risk-free security.

French (1993), Carhart (1997), Hou et al. (2015), and Fama and French (2015). Table 3 shows that these 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 (FF3) that includes MKT, SMB, and HML 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. Approximately 35% of the total variation in AD Bear excess returns cannot be explained by these risk factors.

3.5 Hedged AD Bear Returns

The intercept plus the residual from the CAPM regression in Table 3 can be interpreted as the excess return of the AD Bear portfolio hedged with respect to the market factor (hedged AD Bear portfolio). In Section 2 we demonstrated theoretically that the hedged AD Bear portfolio is highly responsive to bear market risk. Therefore, we expect large CAPM residuals to coincide with economic events affecting investors' forward-looking assessment of future bear market states.[17] In Figure 2, we plot the time-series of residuals from the CAPM regression and indicate the five largest residuals with the numbers 1-5. The largest residual of 34.62% occurs during the five-trading day period between the end of February 26, 2007 and the end of March 5, 2007. During this period, the Chinese stock market crashed – the SSE Composite Index of the Shanghai Stock Exchange experienced a 9% drop on Feb 27, 2007, the largest in 10 years. 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. 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

[17]Since we use the CAPM as the benchmark model, economic events that induce large negative market returns would not be captured by our hedged AD Bear return, which is orthogonalized to the market factor.

"Black Monday" when the Shanghai Composite Index tumbled 8.5%, the biggest loss since February 2007. Finally, the fifth largest residual occurs between 12/29/2014 and 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. Notably, market returns during these five periods are only moderately negative. Therefore, the largest hedged AD Bear returns appear to be associated with important negative economic events, but these events are different from events that drive the largest negative market returns. This is consistent with the notion that bear market risk can increase even in the absence of a realized bear market state.

In summary, Table 3 demonstrates that AD Bear returns have an orthogonal component to the market risk factor (and other commonly used risk factors) that earns a negative and highly statistically significant average premium. Figure 2 shows that large spikes in the hedged AD Bear return correspond to news events that plausibly result in an increase in bear market risk. We caution against relying too heavily on these results because trading the AD Bear portfolio by buying at the ask price and selling at the bid price would incur substantial transaction costs. We therefore interpret the AD Bear returns simply as a measure of bear market risk and proceed to test our main hypothesis, that bear market risk has a negative price of risk, by examining the cross-sectional relation between bear market risk exposure and expected stock returns.

4 Bear Beta and Expected Stock Returns

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

4.1 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

$$R_{i,d} = \beta_0 + \beta_i^{\mathrm{MKT}} \mathrm{MKT}_d + \beta_i^{\mathrm{BEAR}} R_{\mathrm{AD\ Bear},d} + \epsilon_{i,d} \tag{6}$$

where $R_{i,d}$ is the excess return of stock i over the the five-trading-day period ending at the close of day d, MKT_d is the contemporaneous market excess return, and $R_{\mathrm{AD\ Bear},d}$ is the contemporaneous AD Bear excess return.[18] The regression uses overlapping returns for five-day periods ending in months $t-11$ through t, inclusive. We require at least 180 valid observations to estimate the regression. To minimize 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.[19]

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 Amihud (2002) illiquidity (ILLIQ) values that are less than or equal to the 80th percentile month t ILLIQ value among NYSE stocks.[20] Finally, the Large Cap sample is the subset of the All Stocks sample with market capitalization (MKTCAP) values that are greater than or equal to the 50th percentile value of MKTCAP among NYSE stocks.[21] We use the Liquid and Large Cap samples to distinguish between risk pricing and mispricing explanations for our results. Our samples cover the months t (one-month-ahead return months $t+1$) from December 1996 (January 1997) through August 2015 (September 2015). This period is chosen because December 1996 and August 2015 are the first and last months for which β^{BEAR} can be estimated on a full year's worth of data due to the availability of the OM data.

Table 4 presents the time-series averages of monthly cross-sectional summary statistics for β^{BEAR}, MKTCAP, and ILLIQ. In the average month, All Stock sample values of β^{BEAR} range from -1.71 to 2.13, with mean (0.07) and median (0.05) values that are very close to zero and a standard deviation of 0.41. The distribution of β^{BEAR} has a small positive skewness of 0.25. The mean (median) MKTCAP of stocks in the All Stocks sample is $3.2

[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.

[19] In Section III and Table A2 of the online appendix, we present the results of tests using bear beta that is not adjusted using the shrinkage methodology. The results remain very strong among large and liquid stocks. When examining all stocks, the results are slightly weaker, consistent with unadjusted β^{BEAR} being a noisier measure of a stock's true bear beta for illiquid and small stocks.

[20] ILLIQ is calculated following Amihud (2002) as 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.

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

billion (\$308 million), and the mean (median) value of ILLIQ is 197 (4.75). The All Stocks sample has, on average, 4791 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 2042 (1006) stocks in the average month.

4.3 β^{BEAR}-Sorted Portfolios

4.3.1 Post-formation Portfolio Returns

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

Panel A of Table 5 shows that for the All Stocks sample, average excess returns are nearly monotonically decreasing across β^{BEAR} deciles. The β^{BEAR} decile one portfolio generates an average excess return of 0.98% per month and the average excess return of the 10th decile portfolio is -0.15% per month. The β^{BEAR} $10-1$ portfolio average return of -1.13% per month is economically large and highly statistically significant with a NW t-statistic of -2.72.

To examine whether the pattern in the excess returns of the β^{BEAR}-sorted portfolios is a manifestation of exposure to previously identified risk factors, we calculate the abnormal returns of the decile portfolios relative to the CAPM, FF3, FFC, Q and FF5 factor models. The results demonstrate that standard risk factors do not explain the relation between β^{BEAR} and average returns since the alphas exhibit a similar monotonically decreasing pattern across β^{BEAR} deciles and the alpha of the β^{BEAR} $10-1$ portfolio relative to each of the factor models is negative and statistically significant. The β^{BEAR} $10-1$ portfolio generates monthly alpha

[22]The excess return in month $t+1$ is defined as the delisting-adjusted (Shumway (1997)) stock return minus the return of the one-month U.S. Treasury bill in month $t+1$, recorded in percent. If the stock is delisted in month $t+1$, if a delisting return is provided by CRSP, we take the month $t+1$ return of the stock to be the delisting return. If no delisting return is available, then we determine the stock's return based on the delisting code in CRSP. If the delisting code is 500 (reason unavailable), 520 (went to 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%.

of -1.48% per month (t-statistic $= -3.83$), -1.34% (t-statistic $= -4.57$), -1.25% (t-statistic $= -3.81$), -0.82% (t-statistic $= -2.74$), and -0.71% (t-statistic $= -2.49$) relative to the CAPM, FF3, FFC, Q, and FF5 factor models, respectively.

4.3.2 Post-formation Sensitivities to AD Bear

Theoretically, a factor model indicates contemporaneous relations between the true factor loading and expected returns. Our empirical tests have used a pre-formation measure of bear beta (β^{BEAR}) calculated at the end of month t to predict returns in 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. To interpret the results of our empirical analyses as supportive of a risk-based explanation, it is necessary that our portfolios exhibit dispersion in post-formation exposure to bear market risk. To test whether this is the case, we calculate the post-formation sensitivities of the decile portfolio returns to the AD Bear returns by regressing the entire time-series of post-formation five-day overlapping excess returns of the β^{BEAR} decile portfolios on the contemporaneous AD Bear excess return and MKT, as in equation (6).[23]

For sake of comparison, Table 5 presents the value-weighted average value of (pre-formation) β^{BEAR} for each of the decile portfolios. By construction, the value-weighted pre-formation values of β^{BEAR} increase from -0.64 for the first β^{BEAR} decile portfolio to 0.84 for β^{BEAR} decile portfolio 10. In support of a risk factor-based interpretation of the cross-sectional pattern in returns, the results in Table 5 indicate that the β^{BEAR} $10-1$ portfolio has a strong positive post-formation AD Bear sensitivity of 0.21 (t-statistic $= 2.90$). 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.[24]

4.3.3 Subsample Analysis

If the negative cross-sectional relation between β^{BEAR} and future stock returns is truly indicative of a risk pricing effect, we expect the effect to remain strong in liquid and large

[23]The portfolios are still rebalanced at the end of each month t .

[24]The significant dispersion in post-formation AD Bear sensitivity is noteworthy when compared to the lack of post-formation dispersion exhibited by other non-stock return-based sensitivity measures. For example, Table 1 of Ang, Hodrick, Xing, and Zhang (2006) shows that for quintile portfolios formed by sorting on VIX beta, the average difference in pre-formation VIX betas between the fifth and first quintile is 4.27. However, the average difference in post-formation VIX betas is only 0.051, a reduction of almost 99%. Cremers et al. (2015) also find that their pre-formation jump betas are poor predictors of post-formation jump betas.

stocks. On the other hand, if the negative relation between β^{BEAR} and future stock returns captures mispricing, we would expect the relation to be weak or non-existent among liquid and large 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 portfolio tests using our Liquid and Large Cap samples.

Results for the Liquid sample, shown in Panel B of Table 5, are very similar to those of the All Stocks sample. The Liquid sample average portfolio excess returns decrease strongly across β^{BEAR} deciles. The β^{BEAR} $10-1$ portfolio generates an economically large and highly statistically significant average return of -1.08% per month (t-statistic $= -2.36$), with alphas ranging from -1.49% per month (t-statistic $= -3.51$) using the CAPM model to -0.71% per month (t-statistic $= -2.85$) using the FF5 model. The Liquid sample β^{BEAR} $10-1$ portfolio has a post-formation sensitivity of 0.21 (t-statistic $= 2.71$) to AD Bear excess returns, indicating that the portfolio sort is effective at generating assets with strong variation in post-formation exposure to bear market risk.

The Large Cap sample results in Table 5 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, ranging from -1.28% per month (t-statistic $= -2.96$) using the CAPM model to -0.50% per month (t-statistic $= -2.37$) using the FF5 model. Once again, supportive of a risk-based explanation for the pattern in returns, the β^{BEAR} $10-1$ portfolio exhibits a strong positive post-formation sensitivity to the AD Bear excess returns.

5 Robustness

5.1 Bivariate Portfolio Analyses

Having demonstrated a strong negative cross-sectional relation between bear beta and expected stock returns that is not explained by standard risk factors, we proceed to investigate the possibility that this relation can be explained by other risk variables.[25] We use these risk variables as controls and test the robustness of our univariate β^{BEAR} portfolio results by constructing bivariate portfolios that are neutral to a control variable while having variation in β^{BEAR}. Specifically, at the end of each month t, we sort all stocks into ascending control

[25] We describe each risk variable as we discuss the corresponding results. More detailed descriptions of the control variables are provided in Section I of the online appendix.

variable deciles. 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. Next, we compute the average month $t+1$ excess return across the control variable decile portfolios within each β^{BEAR} decile, and refer to this as the bivariate β^{BEAR} decile portfolio excess return. Finally, we calculate the difference in month $t+1$ returns between the bivariate β^{BEAR} decile 10 and decile one portfolios (β^{BEAR} $10-1$ portfolio). Since the bivariate β^{BEAR} decile portfolios have similar values of the control variable, any return pattern across the bivariate β^{BEAR} decile portfolios is unlikely to be driven by the control variable. The results of the bivariate portfolio analyses are shown in Table 7.

We first control for CAPM beta (β^{CAPM}), measured as the the slope coefficient from a one-year rolling window regression of daily excess stock returns on MKT. Table 6 shows that, in all three samples, average β^{CAPM} increases across the univariate β^{BEAR} decile portfolios. Frazzini and Pedersen (2014) show that high (low) CAPM beta stocks generate negative (positive) alphas under standard risk factor models. We thus test whether our results can be explained by the "betting-against-beta" effect. Table 7 shows that, controlling for β^{CAPM}, the CAPM alpha of the bivariate β^{BEAR} $10-1$ portfolio (-0.78% per month) is less negative than that of the univariate β^{BEAR} $10-1$ portfolio (-1.48% per month) in the All Stocks sample. Nevertheless, the CAPM alpha of the bivariate β^{BEAR} $10-1$ portfolio is still large and highly statistically significant (t-statistic $= -3.95$). Furthermore, we observe alphas ranging from -0.53% to -0.77% per month with t-statistics between -2.18 and -2.97 for the bivariate β^{BEAR} $10-1$ portfolio when we benchmark against FF3, FFC, Q, and FF5 models. Restricting the sample to liquid or large cap stocks yields even stronger results. Therefore, controlling for CAPM beta does not explain the negative relation between bear beta and expected returns.

We then investigate whether downside beta studied in Ang, Chen, and Xing (2006) can explain the negative relation between bear beta and expected stock returns. Ang, Chen, and Xing (2006) find a positive relation between average stock returns and downside beta (β^{-}), measured as the slope coefficient from a one-year rolling window regression of daily excess stock returns on MKT using only below-average MKT days. As discussed in the introduction and in Section 2, while both β^{-} and β^{BEAR} are measures of downside risks, they capture economically different sources of risk: β^{-} measures the covariance between the stock return and the market return when a bear state occurs, whereas β^{BEAR} measures the covariance between the stock return and the innovation in the probability of *future* bear states. Since

β^{-} is strongly correlated with CAPM market beta, to control for market risk, Ang, Chen, and Xing (2006) compute relative downside beta, $\beta^{-} - \beta^{\text{CAPM}}$, and show that this measure is also positively related to expected stock returns.[26] Our β^{BEAR} is more comparable to $\beta^{-} - \beta^{\text{CAPM}}$ than β^{-} because, by including the market factor in the time-series regression used to compute β^{BEAR}, we effectively control for exposure to market risk. Consistent with this intuition, Table 6 indicates that the cross-sectional relation between β^{BEAR} and β^{-} is similar to that between β^{BEAR} and β^{CAPM}, likely due to the strong correlation between β^{-} and β^{CAPM}. Once we control for market risk by subtracting CAPM beta from downside beta, we find a negative cross-sectional relation between β^{BEAR} and $\beta^{-} - \beta^{\text{CAPM}}$, suggesting that there is overlap between stocks that lose value when bear market risk increases and stocks that comove more with the market when the market is down. It is therefore plausible that low β^{BEAR} stocks have higher average returns because they have, on average, higher $\beta^{-} - \beta^{\text{CAPM}}$. However, Table 7 shows that controlling for either β^{-} or $\beta^{-} - \beta^{\text{CAPM}}$ cannot explain the negative relation between β^{BEAR} and future stock returns. Specifically, controlling for β^{-} yields β^{BEAR} $10 - 1$ return spreads between -0.75% and -0.48% per month across the three samples, all of which are statistically significant at the 5% level. Controlling for $\beta^{-} - \beta^{\text{CAPM}}$ yields even more negative β^{BEAR} $10 - 1$ monthly return spreads of -0.94% (t-statistic $= -2.31$), -0.94% (t-statistic $= -2.36$), and -0.79% (t-statistic $= -1.86$) in the All Stocks, Liquid, and Large Cap samples, respectively. In all cases, the alphas relative to each of the factor models remain negative, economically large, and statistically significant.[27]

Our next tests examine whether systematic volatility or jump risk can explain the negative relation between bear beta and expected stock returns. Ang, Hodrick, Xing, and Zhang (2006) find that expected stock returns are negatively related to VIX beta ($\beta^{\Delta\text{VIX}}$), measured as the slope coefficient on the change in the VIX index from a one-month rolling window regression of daily excess stock returns on MKT and VIX changes. Cremers et al. (2015) argue that changes in VIX capture a combination of changes in aggregate volatility risk (VOL) and changes in aggregate jump risk (JUMP) and design option portfolios to capture each of these risks. They find that stock-level sensitivities to both VOL (β^{VOL}) and JUMP (β^{JUMP}), each of which is measured as the sum of the coefficients on contemporaneous and lagged JUMP or VOL factor returns from a one-year rolling window regression of excess stock returns, are both negatively related to expected stock returns.[28] Since the AD Bear

[26] In unreported results, we confirm Ang, Chen, and Xing (2006)'s finding that the correlation between β^{-} and β^{CAPM} is above 0.7.

[27] In untabulated results, we find similar results when we compute downside beta using the bottom 25%, 10%, or 5% of market return observations.

[28] We thank Martijn Cremers, Michael Halling, and David Weinbaum for providing us with daily JUMP

portfolio has positive vega (volatility) and gamma (jump) exposure, we expect a positive cross-sectional relation between β^{BEAR} and each of $\beta^{\Delta\text{VIX}}$, β^{VOL}, and β^{JUMP}. Table 6 shows that this is indeed the case, making it plausible that $\beta^{\Delta\text{VIX}}$, β^{VOL}, or β^{JUMP} explains the negative relation between future stock returns and β^{BEAR}. Nevertheless, Table 7 provides little evidence that any of these risk measures fully captures the pricing effect of β^{BEAR}, since the average returns and alphas of the bivariate β^{BEAR} $10-1$ portfolios in all three samples are all greater in magnitude than -0.45% per month and statistically significant.

We then examine two measures of systematic skewness risk. While skewness does not explicitly differentiate between upside and downside risk, it is possible that skewness risk is mostly driven by the left tail of the distribution of the market return. The first measure is coskewness (COSKEW), measured as the slope coefficient on MKT^2 from a 60-month rolling window regression of monthly excess stock returns on MKT and MKT^2, which is shown by Harvey and Siddique (2000) to be negatively related to expected stock returns. Table 6 documents a positive cross-sectional relation between COSKEW and β^{BEAR}, suggesting that COSKEW may potentially capture the β^{BEAR} effect. However, the results of the bivariate portfolio analysis show that controlling for COSKEW does not explain the negative average excess return or alphas of the β^{BEAR} $10-1$ portfolio.

The second measure is skewness beta ($\beta^{\Delta\text{SKEW}}$) proposed in Chang et al. (2013), calculated as the slope coefficient on innovations in aggregate risk-neutral skewness innovations from a regression of daily excess stock returns on daily values of MKT and innovations in aggregate risk-neutral volatility, skewness, and kurtosis.[29] Chang et al. (2013) show that $\beta^{\Delta\text{SKEW}}$ is negatively related to expected stock returns. However, Table 6 shows that average values of $\beta^{\Delta\text{SKEW}}$ tend to be lower for the high β^{BEAR} deciles, suggesting that controlling for $\beta^{\Delta\text{SKEW}}$ is unlikely to explain the negative cross-sectional relation between β^{BEAR} and future stock returns. Indeed, the results in Table 7 show that the average excess return and alphas of the bivariate β^{BEAR} $10-1$ portfolio constructed to be neutral to $\beta^{\Delta\text{SKEW}}$ remain negative, large in magnitude, and statistically significant.

Finally, we control for two risk measures that are computed directly from individual stock

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).

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

returns. First, Kelly and Jiang (2014) measure tail risk by aggregating large daily losses on individual stocks and calculate tail beta (β^{TAIL}) by regressing stock returns on lagged tail risk. Table 6 shows that average values of β^{TAIL} do not exhibit a strong pattern across the deciles of β^{BEAR}. The results of the bivariate portfolio analyses in Table 7 show that after controlling for β^{TAIL}, the β^{BEAR} $10-1$ portfolio still generates economically large, negative, and highly statistically significant average excess returns and alphas. Second, Ang, Hodrick, Xing, and Zhang (2006) find that idiosyncratic volatility (IVOL), calculated as the standard deviation of the residuals from a one-month rolling window regression of daily excess stock returns on MKT, SMB, and HML, is negatively related to the cross-section of future stock returns. Table 6 shows that average values of IVOL do not exhibit a strong cross-sectional relation with β^{BEAR} and, not surprisingly therefore, the bivariate portfolio analysis results in Table 7 show that controlling for IVOL cannot explain the negative relation between β^{BEAR} and future stock returns.

5.2 Fama-MacBeth Regression Analyses

Bivariate portfolio analysis allows us to control for the effect of one variable at a time when examining the relation between bear beta and expected stock returns. To control for multiple potentially confounding effects simultaneously, we use FM regression analyses. Each month t, we run the following cross-sectional regression:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t}^{\text{BEAR}} + \mathbf{\Lambda_t X_{i,t}} + \epsilon_{i,t} \tag{7}$$

where $R_{i,t+1}$ is stock i's month $t+1$ excess return, $\beta_{i,t}^{\text{BEAR}}$ is stock i's month t value of β^{BEAR}, and $\mathbf{X_{i,t}}$ is a vector of control variables for stock i measured at the end of month t. All independent variables are winsorized at the 0.5 and 99.5% levels on a monthly basis. Our main hypothesis predicts that stocks with higher bear betas earn lower average returns and thus the average regression coefficient on β^{BEAR} should be negative.[30] If the pricing effect of bear beta is distinct from the phenomena captured by the control variables, the coefficient on β^{BEAR} should remain negative when controls are included in the regression specification. Table 8 presents the time-series averages of the monthly cross-sectional regression coefficients along with NW-adjusted t-statistics testing the null hypothesis that the time-series average is equal to zero.

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

We begin with two baseline specifications. Specification (1) has β^{BEAR} as the only independent variable. The average coefficient on β^{BEAR} is -0.45 (t-statistic = -2.40), -0.67 (t-statistic = -2.68), and -0.80 (t-statistic = -2.82) in the All Stocks, Liquid, and Large Cap sample, respectively, each of which is negative and statistically significant. This is consistent with the univariate portfolio results and indicates a strong negative relation between bear beta and expected stock returns. We next control for exposure to CAPM market risk by including β^{CAPM} as the second independent variable (specification (2)). This specification is comparable to the bivariate portfolio analysis that controls for β^{CAPM}. Table 8 shows that, although the average coefficient on β^{BEAR} is slightly lower (compared to the univariate specification) when controlling for β^{CAPM}, it remains negative and highly statistically significant in all three samples. As was the case when using bivariate portfolio analysis, the FM regression analysis indicates that the negative cross-sectional relation between β^{BEAR} and future stock returns is not explained by exposure to market risk.

The remaining regression specifications augment specification (2) by including additional controls. We add β^{-} in specification (3), $\beta^{\Delta\text{VIX}}$ in specification (4), β^{JUMP} and β^{VOL} in specification (5), COSKEW in specification (6), $\beta^{\Delta\text{SKEW}}$ in specification (7), β^{TAIL} in specification (8), and IVOL in specification (9). In each of these specifications, the average coefficient on β^{BEAR} remains negative and statistically significant at the 5% level in all three samples, with the only exception being specification (7) in the All Stocks sample, which produces an average coefficient on β^{BEAR} that is negative and significant at the 10% level.[31] In all specifications other than specification (9) that includes IVOL, the coefficients on the control variables are not statistically significant.

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

Finally, in specification (11), we also control for firm-level characteristics that have previously been shown to be related to expected stock returns. Specifically, we add SIZE (log of MKTCAP), the log of the book-to-market ratio (BM), momentum (MOM), illiquidity

[31]The decreased statistical significance is likely because values of $\beta^{\Delta\text{SKEW}}$ are only available for the 133 months from December 1996 through December 2007, thus limiting the power of the test. In the Liquid and Large Cap samples, the limited of power of the test is overcome by a more negative average coefficient, resulting in larger t-statistics.

(ILLIQ), profitability (Y), and investment (INV) as additional control variables.[32] In our portfolio analyses, we controlled for the impact of size, value, momentum, profitability, and investment on expected stock returns by adjusting the portfolio returns for exposures to corresponding factors.[33] Our use of the Liquid and Large Cap samples in the portfolio analyses controls for the liquidity effect. It is therefore not surprising that adding the additional characteristic controls to the regression specification does not explain the negative relation between β^{BEAR} and future stock returns. In specification (11), which includes the full set of controls, the average coefficient on β^{BEAR} is -0.29 (t-statistic $= -2.84$), -0.29 (t-statistic $= -2.28$), and -0.41 (t-statistic $= -2.30$) in the All Stocks, Liquid, and Large Cap sample, respectively, each of which remains highly significant.[34]

The main takeaway from the results in Table 8 is clear. There is a strong 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. As a final robustness test, we examine the possibility that the negative cross-sectional relation between β^{BEAR} and future stock returns is driven by the financial crisis of 2007 through 2009 by excluding the return months from December 2007 through June 2009, a period identified by the NBER as recessionary, and rerunning the FM regression analyses. The results, presented in Section IV and Table A3 of the online appendix, demonstrate that the negative relation between β^{BEAR} and future stock returns remains strong when the crisis period is excluded.

5.3 Predictive Power Beyond One Month

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

[32] BM is calculated following Fama and French (1992). MOM is the 11-month stock return in months $t-11$ through $t-1$ inclusive (skipping month t). Y and INV are calculated following Fama and French (2015).

[33] In untabulated results, we add short-term reversal (Jegadeesh (1990)) and the maximum daily return (Bali et al. (2011), Bali et al. (Forthcoming)) to specification (11) and show that our results are robust to the inclusion of these additional controls.

[34] Consistent with previous research, our regressions detect a negative relation between future stock returns and SIZE, a positive relation between future stock returns and Y, except in the Large Cap sample, and a positive relation between future stock returns and ILLIQ in the All Stocks sample. The average coefficients on BM, MOM, and INV are insignificant in our sample period.

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

Table 9 presents the average coefficients on β^{BEAR} from these regressions (to save space, we do not report intercept or control variable coefficients). The univariate regressions (specification (1)) show that the relation between β^{BEAR} and future stock returns remains negative and statistically significant when using 2- to 6-month ahead excess returns across all three samples. Adding control variables has little impact on the results. When all risk variables are included as independent variables in specification (10), the average coefficients on β^{BEAR} remain significant at the 5% level for all forecasting horizons across the three samples. When all risk variables and characteristics are included (specification (11)), we find the average coefficients on β^{BEAR} remain negative and significant at the 5% level in all cases except when using month $t + 4$ or $t + 5$ excess returns in the Liquid sample (t-statistics of -1.82 and -1.83, respectively) and month $t + 4$ excess returns in the Large Cap sample (t-statistic $= -1.81$), which are significant at the 10% level. The results indicate that the negative cross-sectional relation between β^{BEAR} and future stock returns is strong for at least six months into the future.

6 Conclusion

In summary, we examine the hypothesis that time-variation in the probability of future bear market states, which we refer to as bear market risk, is a priced risk factor. We construct a theoretically motivated option portfolio, AD Bear, that pays off \$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 market risk is priced in the cross section of stocks by examining the relation between bear beta – stock-level sensitivity to AD Bear portfolio returns – and expected stock returns. Portfolio and regression analyses demonstrate that high-bear beta stocks, i.e. stocks that outperform when bear market risk increases, earn low average returns. This negative cross-sectional relation between bear beta and expected stock returns remains strong after controlling for a battery of previously documented risk and characteristic-based pricing effects. Supportive of a risk-based interpretation of our results, portfolios sorted on bear beta exhibit strong cross-sectional variation in post-formation exposure to AD Bear returns, the negative relation between bear beta and future stock returns remains strong even when the sample is restricted to liquid and large cap stocks, and the return predictability persists for at least six months into the future. We conclude that 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, $X_T = 1\left\{\frac{F_T}{F_0} \leq K\right\}$, where time 0 is the portfolio formation day and F_0 is the T-year forward price at time 0. 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 solution that delivers transparent economic intuition.

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

$$
\begin{aligned}
dX_t &= X_t - X_0 \\
&= E_t^Q\left(1\left\{\frac{F_T}{F_0}\leq K\right\}\right)e^{-r(T-t)} - E_0^Q\left(1\left\{\frac{F_T}{F_0}\leq K\right\}\right)e^{-rT} \qquad \text{(A.4)} \\
&= \left[E_t^Q\left(1\left\{\frac{F_T}{F_0}\leq K\right\}\right) - E_0^Q\left(1\left\{\frac{F_T}{F_0}\leq K\right\}\right)\right]e^{-r(T-t)} \\
&+ E_0^Q\left(1\left\{\frac{F_T}{F_0}\leq K\right\}\right)\left(e^{-r(T-t)} - e^{-rT}\right) \\
&= \left[E_t^Q\left(1\left\{\frac{F_T}{F_0}\leq K\right\}\right) - E_0^Q\left(1\left\{\frac{F_T}{F_0}\leq K\right\}\right)\right]e^{-r(T-t)} + X_0\left(e^{rt}-1\right) \qquad \text{(A.5)}
\end{aligned}
$$

Letting $P_t = E_t^Q\left(1\left\{\frac{F_T}{F_0}\leq K\right\}\right)$ gives

$$
dX_t = dP_t e^{-r(T-t)} + X_0\left(e^{rt}-1\right). \qquad \text{(A.6)}
$$

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

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

$$
P_t \;=\; E_t^Q\left(1\left\{\phi log\left(C_T\right) + b_{F,\lambda}\lambda_T \leq log\left(K\right) + \phi log\left(C_0\right) + b_{F,\lambda}\lambda_0\right\}\right). \qquad \text{(A.7)}
$$

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:

$$
\lambda_T \sim N\left(\left(1-e^{-\kappa(T-t)}\right)\overline{\lambda} + \lambda_t e^{-\kappa(T-t)}, \frac{\sigma_\lambda^2\lambda_t}{2\kappa}\left(1-e^{-2\kappa(T-t)}\right)\right). \qquad \text{(A.8)}
$$

Using these two approximations, we get an analytical solution.

$log\left(C_T\right)$ follows a normal distribution with mean $log\left(C_t\right) + \left(\mu - \frac{1}{2}\sigma^2\right)\left(T-t\right)$ and variance $\sigma^2\left(T-t\right)$ if there is no jump. We assume Z_t is of constant size $\mu_Z < 0$. Following Merton (1976), we know that conditional on $N_T - N_t = n$,

$$
\phi log\left(C_T\right) + b_{F,\lambda}\lambda_T \;\sim\; N\left(\mu_n, \nu^2\right) \qquad \text{(A.9)}
$$

where

$$\mu_n = \mu^Q + \phi log\left(C_t\right) + n\phi\mu_Z + b_{F,\lambda}\lambda_t e^{-\kappa(T-t)}, \tag{A.10}$$

$$\nu^2 = \phi^2\sigma^2\left(T-t\right) + b_{F,\lambda}^2 \frac{\sigma_\lambda^2\lambda_t}{2\kappa}\left(1-e^{-2\kappa(T-t)}\right), \tag{A.11}$$

and μ^Q captures the drift term under the Q measure that is unrelated to λ_t, $log\left(C_t\right)$, or Z_t .

Therefore,

$$P_t = \sum_{n=0}^{\infty} \frac{e^{-\lambda_t(T-t)}\left(\lambda_t\left(T-t\right)\right)^n}{n!} N\left(d_n\right) \tag{A.12}$$

where

$$d_n = \frac{log\left(K\right) + \phi log\left(C_0\right) + b_{F,\lambda}\lambda_0 - \mu_n}{\nu} \tag{A.13}$$

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 $\frac{\partial d_n}{\partial B_t} = -\frac{\phi\sigma}{\nu}$, we have

$$\begin{aligned} \frac{\partial P_t}{\partial B_t} &= \sum_{n=0}^{\infty} \frac{e^{-\lambda_t(T-t)}\left(\lambda_t\left(T-t\right)\right)^n}{n!} N'\left(d_n\right) \times \left(-\frac{\phi\sigma}{\nu}\right) \\ &= e^{-\lambda_t(T-t)}\left(\sum_{n=0}^{\infty}\delta_n\right) \times \left(-\frac{\phi\sigma}{\nu}\right) \end{aligned} \tag{A.14}$$

where

$$\delta_n = \frac{\left(\lambda_t\left(T-t\right)\right)^n}{n!} \frac{1}{\sqrt{2\pi}} exp\left(-\frac{1}{2}d_n^2\right). \tag{A.15}$$

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

$$\frac{\partial P_t}{\partial J_t} = e^{-\lambda_t(T-t)}\left(\sum_{n=0}^{\infty}\delta_n\right) \times -\frac{\phi\mu_Z}{\nu} + o\left(Z_t\right) \tag{A.16}$$

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

$$\frac{\partial d_n}{\partial B_{\lambda,t}} = \left[-\frac{b_{F,\lambda}e^{-\kappa(T-t)}}{\nu} - \frac{d_n b_{F,\lambda}^2 \frac{\sigma_\lambda^2}{2\kappa}\left(1-e^{-2\kappa(T-t)}\right)}{\nu}\right]\sigma_\lambda\sqrt{\lambda_t} \tag{A.17}$$

we have

$$\begin{aligned}
\frac{\partial P_t}{\partial B_{\lambda,t}} &= \sum_{n=0}^{\infty}\frac{\partial e^{-\lambda_t(T-t)}\left(\lambda_t\left(T-t\right)\right)^n}{\partial\lambda_t}N\left(d_n\right)\times\sigma_\lambda\sqrt{\lambda_t}+e^{-\lambda_t(T-t)}\left(\sum_{n=0}^{\infty}\delta_n\right)\times\frac{\partial d_n}{\partial B_{\lambda,t}} \\
&= \sum_{n=0}^{\infty}\left(\frac{\left(\lambda_t\left(T-t\right)\right)^{n-1}}{(n-1)!}-\frac{\left(\lambda_t\left(T-t\right)\right)^n}{n!}\right)N\left(d_n\right)\times\sigma_\lambda\sqrt{\lambda_t}\times e^{-\lambda_t(T-t)}\left(T-t\right) \\
&\quad +e^{-\lambda_t(T-t)}\left(\sum_{n=0}^{\infty}\delta_n\right)\times\frac{\partial d_n}{\partial B_{\lambda,t}} && \text{(A.18)} \\
&= \sum_{n=1}^{\infty}\frac{\left(\lambda_t\left(T-t\right)\right)^{n-1}}{(n-1)!}\left[N\left(d_n\right)-N\left(d_{n-1}\right)\right]\times\sigma_\lambda\sqrt{\lambda_t}\times e^{-\lambda_t(T-t)}\left(T-t\right) && \text{(A.19)} \\
&\quad +e^{-\lambda_t(T-t)}\left(\sum_{n=0}^{\infty}\delta_n\right)\times\frac{\partial d_n}{\partial B_{\lambda,t}}. && \text{(A.20)}
\end{aligned}$$

Again, ignoring the second and higher-order effects of Z_t, we have $N\left(d_n\right)-N\left(d_{n-1}\right) = N'\left(d_{n-1}\right)\frac{-\phi\mu_Z}{\nu}$ and thus

$$\begin{aligned}
\frac{\partial P_t}{\partial B_{\lambda,t}} &= e^{-\lambda_t(T-t)}\left(T-t\right)\left[\sum_{n=0}^{\infty}\delta_n\frac{-\phi\mu_Z}{\nu}\right]\times\sigma_\lambda\sqrt{\lambda_t}+e^{-\lambda_t(T-t)}\left(\sum_{n=0}^{\infty}\delta_n\right)\times\frac{\partial d_n}{\partial B_{\lambda,t}} \\
&= e^{-\lambda_t(T-t)}\left(\sum_{n=0}^{\infty}\delta_n\right)\times\left\{-\left(T-t\right)\phi\mu_Z-\frac{b_{F,\lambda}e^{-\kappa(T-t)}}{\nu}-\frac{d_n b_{F,\lambda}^2\frac{\sigma_\lambda^2}{2\kappa}\left(1-e^{-2\kappa(T-t)}\right)}{\nu}\right\}\times\sigma_\lambda\sqrt{\lambda_t}.
\end{aligned} \tag{A.21}$$

Appendix B Bayes Shrinkage Method

We implement the Bayes shrinkage methodology as follows. First, for each stock i and month t, we run the regression specified in equation (6) as deccribed in Section 4.1. We let $\beta_{\text{OLS},i,t}^{\text{BEAR}}$ be the estimated coefficient on $R_{\text{AD Bear},d}$ and $\sigma_{\text{OLS},i,t}^2$ be the variance of the OLS estimate $\beta_{\text{OLS},i,t}^{\text{BEAR}}$. For each month t we take the prior mean, $\beta_{\text{Prior},t}^{\text{BEAR}}$, to be the average $\beta_{\text{OLS},i,m}^{\text{BEAR}}$ across all stock-month observations in months m between December 1996 and month t, inclusive. Similarly, we take the prior variance, $\sigma^2_{\text{Prior},t}$ to be the sample variance of $\beta^{\text{BEAR}}_{\text{OLS},i,m}$ over the same period. That is,

$$\beta^{\text{BEAR}}_{\text{Prior},t} = \frac{\sum_{m\leq t,i} \beta^{\text{BEAR}}_{\text{OLS},i,m}}{n_t} \tag{B.1}$$

and

$$\sigma^2_{\text{Prior},t} = \frac{\sum_{m\leq t,i} \left(\beta^{\text{BEAR}}_{\text{OLS},i,m} - \beta^{\text{BEAR}}_{\text{Prior},t}\right)^2}{n_t - 1} \tag{B.2}$$

where n_t is the number of stock-month observations with valid values of $\beta^{\text{BEAR}}_{\text{OLS},i,m}$ over all months m between December 1996 and month t, inclusive. Finally, the Bayes-adjusted value of bear beta that we use as our focal variable throughout the paper is the inverse-variance-weighted average of the OLS estimate and the prior mean:

$$\beta^{\text{BEAR}}_{i,t} = \frac{\left(\sigma^2_{\text{OLS},i,t}\right)^{-1}}{\left(\sigma^2_{\text{OLS},i,t}\right)^{-1} + \left(\sigma^2_{\text{Prior},t}\right)^{-1}}\beta^{\text{BEAR}}_{\text{OLS},i,t} + \frac{\left(\sigma^2_{\text{Prior},t}\right)^{-1}}{\left(\sigma^2_{\text{OLS},i,t}\right)^{-1} + \left(\sigma^2_{\text{Prior},t}\right)^{-1}}\beta^{\text{BEAR}}_{\text{Prior},t}. \tag{B.3}$$

The following brief theoretical derivation clarifies the priors we use. We assume that the error term in equation (6) follows a normal distribution: $\epsilon_{i,d} \sim N\left(0, \nu_i^2\right)$. We also assume that the prior distribution of β^{BEAR}_i is normal: $\beta^{\text{BEAR}}_i | \nu_i^2, \beta^{\text{MKT}}_i \sim N\left(\beta_{\text{Prior}}, \sigma^2_{\text{Prior}}\right)$. The posterior distribution of β^{BEAR}_i then follows a normal distribution $\beta^{\text{BEAR}}_i | \sigma_i^2, \beta^{\text{MKT}}_i, \{R_{i,d}\} \sim N\left(\widetilde{\beta^{\text{BEAR}}_i}, \widetilde{\Sigma^{\text{BEAR}}_i}\right)$ with the posterior mean

$$\begin{aligned}
\widetilde{\beta^{\text{BEAR}}_i} &= \beta_{\text{Prior}} + \left(\sigma^{-2}_{\text{Prior}} + \sigma^{-2}\left(\beta^{\text{BEAR}}_{\text{OLS},i}\right)\right)^{-1} \sigma^{-2}\left(\beta^{\text{BEAR}}_{\text{OLS},i}\right)\left(\beta^{\text{BEAR}}_{\text{OLS},i} - \beta_{\text{Prior}}\right) \\
&= \frac{\left(\sigma^2_{\text{OLS},i}\right)^{-1}}{\left(\sigma^2_{\text{OLS},i}\right)^{-1} + \left(\sigma^2_{\text{Prior}}\right)^{-1}}\beta^{\text{BEAR}}_{\text{OLS},i} + \frac{\left(\sigma^2_{\text{Prior}}\right)^{-1}}{\left(\sigma^2_{\text{OLS},i}\right)^{-1} + \left(\sigma^2_{\text{Prior}}\right)^{-1}}\beta^{\text{BEAR}}_{\text{Prior}}.
\end{aligned} \tag{B.4}$$

Intuitively, $\widetilde{\beta^{\text{BEAR}}_i}$ shrinks the OLS estimate $\beta^{\text{BEAR}}_{\text{OLS},i}$ toward β_{Prior} to account for sampling errors. Higher (lower) OLS sampling errors, captured by $\sigma^2_{\text{OLS},i}$, result in more (less) weight being placed on β_{Prior} and less (more) weight being placed on $\beta^{\text{BEAR}}_{\text{OLS},i}$.

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. Forthcoming. A lottery demand-based explanation of the beta anomaly. Journal of Financial and Quantitative Analysis.

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.

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.

Bollerslev, T. and Todorov, V. 2011. Tails, fears, and risk premia. The Journal of Finance, 66(6), 2165–2211.

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

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

Carr, P. and Wu, L. 2011. A simple robust link between american puts and credit protection. Review of Financial Studies, 24(2), 473–505.

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.

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.

Figlewski, S. Estimating the implied risk neutral density for the U.S. market portfolio. In T. Bollerslev, J. Russel, and M. Watson, editors, *Volatility and Time Series Econometrics: Essays in Honor of Robert Engle.* Oxford University Press, Oxford, 2010.

Frazzini, A. and Pedersen, L. H. 2014. Betting against beta. Journal of Financial Economics, 111(1), 1–25.

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

Harvey, C. R. 2017. The scientific outlook in financial economics. SSRN eLibrary.

Harvey, C. R., Liu, Y., and Zhu, H. 2015. ... and the cross-section of expected returns. Review of Financial Studies, forthcoming.

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.

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.

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).

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.

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

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 solid black line shows the payoff function of the AD Bear portfolio. The dashed red line shows the payoff function of the long put position. The dotted green line shows the payoff function of the short put position. The dash-dotted blue line shows the payoff function of the theoretical AD Bear portfolio.

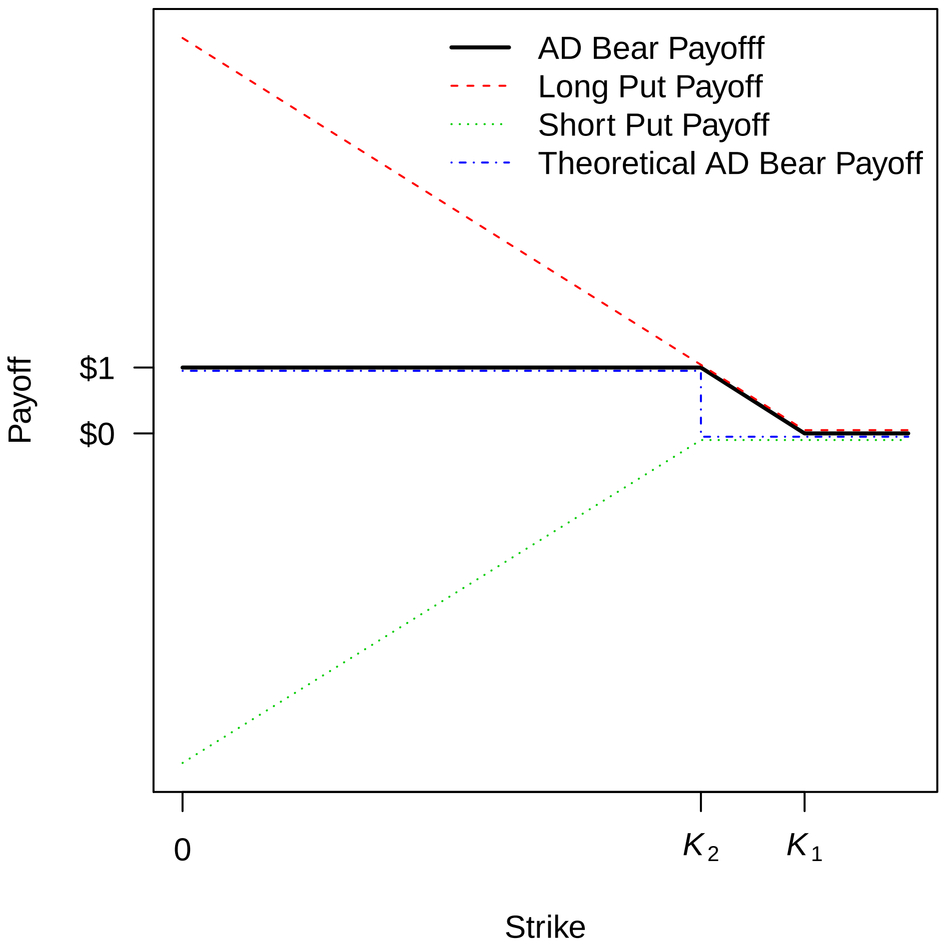

Figure 2: AD Bear CAPM Residuals

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.

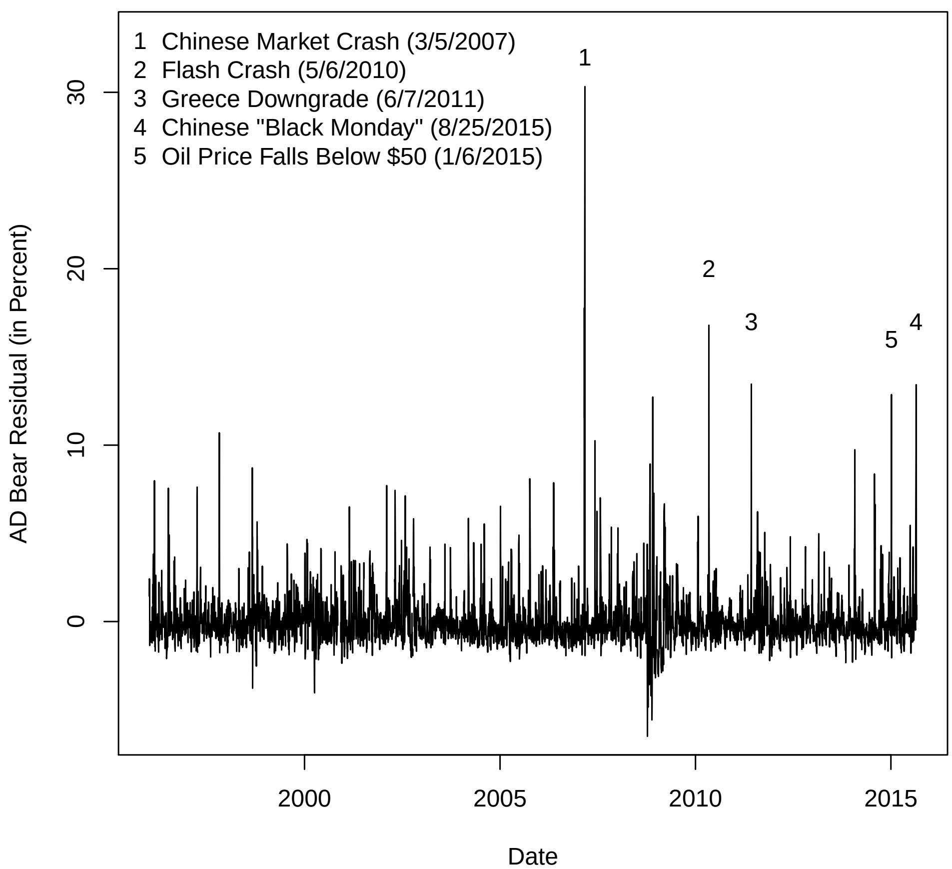

Table 1: Sensitivities of Market Portfolio and AD Bear Returns to Three Sources of Fundamental Risk

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 (2013)'s model derived using a first-order Taylor expansion. dB_t is a standard Brownian motion capturing continuous consumption shocks. Z_t is the realized consumption jump at time t. $dB_{\lambda,t}$ is the shock to the time-varying intensity of future jumps. $\Delta = e^{-\lambda_t \tau} \left(\sum_{n=0}^{\infty} \delta_n\right) \nu^{-1}$ is the ratio between the sensitivity of $\frac{dX_t}{X_t}$ to dB_t and the sensitivity of $\frac{dF_t}{F_t}$ to dB_t. Refer to equations (1) and (2), and associated text, for more parameter definitions. Hedged AD Bear Return is the return of 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. $b_{F,\lambda}$ is negative. γ, ϕ, $b_{\pi,\lambda}$ and $b_{X,\lambda}$ are positive.

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

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 standard risk factors. The unscaled AD Bear excess returns (AD Bear (Unscaled)) are the actual excess returns generated by the AD Bear portfolio. The scaled (AD Bear) excess returns are the unscaled excess returns divided by 28.87836. The scaling factor 28.87836 is chosen so that the standard deviation of the scaled AD Bear excess returns is equal to the standard deviation of the MKT factor returns. The five-day excess returns of MKT, SMB, HML, MOM, SMB_5, RMW, CMA, ME, IA, and ROE are calculated by first compounding the daily gross returns of the factors over a five-day period and then subtracting the contemporaneous five-day risk free rate. The table presents the mean (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 time-series regressions of AD Bear portfolio excess returns on standard factors. The table shows the intercept coefficient (Excess Return or α), slope coefficients (β), and adjusted R-squared (Adj. R^2). t-statistics, adjusted following Newey and West (1987) using 22 lags, testing the null hypothesis of a zero intercept or slope coefficient, are shown in parentheses below the corresponding coefficient. The regressions include the 4910 valid five-day AD Bear excess return observations during the period from January 11, 1996 through August 31, 2015.

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%

Table 4: Summary Statistics

The table below presents cross-sectional summary statistics for bear beta (β^{BEAR}), market capitalization (MKTCAP), and Amihud (2002) illiquidity (ILLIQ). The All Stocks sample includes 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. This table shows 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. The summary statistics cover the 225 months t from December 1996 through August 2015.

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

Table 5: β^{BEAR}-Sorted Portfolios Returns

The table below presents the results of univariate portfolio analyses of the relation between β^{BEAR} and future stock returns. Each month t, all stocks in the sample are sorted into decile portfolios based on an ascending sort of β^{BEAR}. The columns labeled "β^{BEAR} 1" through "β^{BEAR} 10" present results for the first through 10th β^{BEAR} decile portfolios. 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. Newey and West (1987)-adjusted t-statistics using 12 lags are presented in parentheses. The row labeled "Pre-Formation" shows the time-series average of the monthly value-weighted average values of pre-formation β^{BEAR} for each of the portfolios. The row labeled "Post-Formation" presents the corresponding post-formation β^{BEAR}, calculated as the slope coefficient on AD Bear portfolio excess returns from a regression of the daily five-day overlapping portfolio excess returns on the contemporaneous MKT and AD Bear portfolio excess returns. t-statistics reported in parentheses for the post-formation sensitivities are adjusted following Newey and West (1987) using 22 lags. Panels A, B, and C present results for the All Stocks, Liquid, and Large Cap samples, respectively.

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	0.98	0.82	0.66	0.47	0.62	0.41	0.48	0.39	0.32	−0.15	−1.13
		(2.62)	(2.76)	(2.32)	(1.58)	(1.76)	(1.02)	(1.14)	(0.77)	(0.59)	(−0.23)	(−2.72)
CAPM	α	0.47	0.36	0.22	0.01	0.10	−0.13	−0.09	−0.24	−0.42	−1.02	−1.48
		(2.45)	(2.12)	(1.57)	(0.08)	(1.26)	(−0.82)	(−0.81)	(−1.24)	(−2.14)	(−3.82)	(−3.83)
FF3	α	0.39	0.31	0.20	−0.01	0.12	−0.08	−0.04	−0.23	−0.39	−0.95	−1.34
		(2.48)	(2.33)	(1.82)	(−0.07)	(1.41)	(−0.62)	(−0.40)	(−1.32)	(−2.58)	(−4.83)	(−4.57)
FFC	α	0.42	0.34	0.21	0.02	0.12	−0.09	−0.03	−0.17	−0.34	−0.83	−1.25
		(2.41)	(2.65)	(1.80)	(0.14)	(1.19)	(−0.70)	(−0.34)	(−0.99)	(−1.97)	(−3.99)	(−3.81)
Q	α	0.31	0.24	0.17	0.06	0.15	0.04	0.01	−0.07	−0.18	−0.51	−0.82
		(1.78)	(1.93)	(1.37)	(0.38)	(1.12)	(0.35)	(0.06)	(−0.44)	(−1.13)	(−2.48)	(−2.74)
FF5	α	0.24	0.21	0.06	−0.02	0.12	−0.01	0.05	−0.04	−0.12	−0.47	−0.71
		(1.34)	(1.69)	(0.78)	(−0.19)	(1.27)	(−0.08)	(0.48)	(−0.31)	(−1.03)	(−2.35)	(−2.49)
	β_{MKT}	1.10	1.01	0.94	0.91	0.99	0.97	1.02	1.07	1.20	1.25	0.15
		(20.51)	(17.40)	(33.46)	(16.64)	(31.64)	(26.34)	(28.93)	(21.58)	(19.20)	(16.07)	(1.35)
	β_{SMB_5}	0.02	−0.16	−0.05	0.01	−0.04	0.04	−0.00	0.13	0.24	0.40	0.37
		(0.28)	(−2.18)	(−0.93)	(0.12)	(−1.00)	(0.90)	(−0.02)	(2.45)	(3.20)	(3.85)	(2.62)
	β_{HML}	0.10	0.08	−0.04	0.05	−0.04	−0.12	−0.14	0.04	0.05	−0.10	−0.20
		(0.82)	(0.77)	(−0.80)	(0.44)	(−0.67)	(−2.45)	(−2.03)	(0.42)	(0.47)	(−0.61)	(−0.80)
	β_{RMW}	0.11	0.04	0.17	0.04	−0.01	−0.06	−0.15	−0.24	−0.31	−0.76	−0.87
		(0.59)	(0.25)	(1.64)	(0.64)	(−0.27)	(−0.85)	(−2.19)	(−1.83)	(−2.41)	(−5.70)	(−2.93)
	β_{CMA}	0.39	0.36	0.26	−0.00	0.01	−0.17	−0.10	−0.31	−0.59	−0.62	−1.01
		(1.59)	(1.58)	(3.16)	(−0.02)	(0.06)	(−1.03)	(−0.82)	(−1.84)	(−4.52)	(−2.45)	(−2.35)
Pre-Formation	β^{BEAR}	−0.64	−0.33	−0.19	−0.09	0.01	0.10	0.19	0.31	0.47	0.84	1.48
Post-Formation	β^{BEAR}	−0.05	−0.03	−0.03	−0.03	−0.01	−0.00	0.03	0.11	0.16	0.18	0.21
		(−1.66)	(−0.92)	(−1.35)	(−1.73)	(−0.53)	(−0.23)	(1.29)	(2.89)	(3.64)	(3.17)	(2.90)

Table 5: β^{BEAR}-Sorted Portfolios Returns - 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	0.90	0.79	0.69	0.67	0.56	0.35	0.46	0.37	0.35	−0.18	−1.08
		(2.60)	(2.69)	(2.41)	(2.24)	(1.54)	(0.82)	(1.14)	(0.73)	(0.70)	(−0.27)	(−2.36)
CAPM	α	0.42	0.35	0.25	0.23	0.05	−0.22	−0.11	−0.27	−0.38	−1.07	−1.49
		(2.49)	(2.08)	(1.64)	(1.46)	(0.55)	(−1.38)	(−0.76)	(−1.45)	(−1.86)	(−3.51)	(−3.51)
FF3	α	0.35	0.32	0.23	0.20	0.06	−0.15	−0.05	−0.23	−0.35	−0.98	−1.33
		(2.81)	(2.28)	(1.70)	(1.58)	(0.66)	(−1.30)	(−0.50)	(−1.58)	(−2.47)	(−4.79)	(−5.01)
FFC	α	0.38	0.35	0.21	0.19	0.08	−0.11	−0.04	−0.16	−0.26	−0.84	−1.23
		(2.84)	(2.45)	(1.51)	(1.44)	(0.75)	(−0.85)	(−0.34)	(−1.08)	(−1.65)	(−3.75)	(−4.08)
Q	α	0.30	0.25	0.13	0.12	0.08	−0.04	0.02	−0.08	−0.09	−0.55	−0.85
		(2.09)	(1.65)	(1.04)	(0.87)	(0.61)	(−0.38)	(0.24)	(−0.49)	(−0.61)	(−2.45)	(−3.11)
FF5	α	0.22	0.21	0.06	0.10	0.06	−0.11	0.07	−0.03	−0.06	−0.49	−0.71
		(1.36)	(1.55)	(0.58)	(0.90)	(0.59)	(−0.94)	(0.74)	(−0.20)	(−0.53)	(−2.81)	(−2.85)
	β_{MKT}	1.04	0.97	0.99	0.93	0.99	1.03	1.00	1.10	1.19	1.31	0.27
		(19.97)	(20.96)	(19.98)	(46.61)	(25.52)	(34.07)	(30.45)	(22.54)	(18.90)	(15.02)	(2.39)
	β_{SMB_5}	−0.04	−0.19	−0.14	−0.03	−0.04	−0.01	−0.03	0.05	0.21	0.29	0.33
		(−0.48)	(−2.61)	(−2.46)	(−0.44)	(−0.98)	(−0.20)	(−0.57)	(0.73)	(2.35)	(2.55)	(2.13)
	β_{HML}	0.09	0.06	−0.02	0.02	0.06	−0.14	−0.11	0.04	0.06	−0.09	−0.18
		(0.96)	(0.56)	(−0.24)	(0.39)	(0.92)	(−2.78)	(−1.73)	(0.42)	(0.54)	(−0.53)	(−0.78)
	β_{RMW}	0.11	0.06	0.21	0.14	0.09	0.02	−0.15	−0.25	−0.31	−0.72	−0.83
		(0.58)	(0.49)	(2.78)	(1.93)	(1.45)	(0.43)	(−1.52)	(−1.86)	(−1.93)	(−5.22)	(−2.80)
	β_{CMA}	0.35	0.34	0.30	0.17	−0.15	−0.22	−0.22	−0.38	−0.61	−0.70	−1.05
		(1.40)	(2.02)	(2.05)	(2.86)	(−1.05)	(−1.36)	(−1.72)	(−2.26)	(−4.06)	(−2.79)	(−2.41)
Pre-Formation	β^{BEAR}	−0.56	−0.28	−0.16	−0.06	0.02	0.11	0.20	0.31	0.47	0.81	1.36
Post-Formation	β^{BEAR}	−0.04	−0.04	−0.05	−0.01	−0.04	−0.00	0.02	0.10	0.16	0.18	0.21
		(−1.38)	(−1.33)	(−2.03)	(−0.76)	(−2.21)	(−0.04)	(0.71)	(2.04)	(3.73)	(3.10)	(2.71)

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	0.83	0.80	0.64	0.57	0.67	0.60	0.35	0.27	0.25	−0.07	−0.90
		(2.46)	(2.86)	(2.26)	(1.78)	(2.20)	(1.80)	(0.81)	(0.60)	(0.47)	(−0.11)	(−2.06)
CAPM	α	0.36	0.37	0.23	0.14	0.22	0.11	−0.20	−0.31	−0.43	−0.92	−1.28
		(2.36)	(2.78)	(1.25)	(0.91)	(1.57)	(1.23)	(−1.41)	(−1.72)	(−1.82)	(−2.82)	(−2.96)
FF3	α	0.31	0.36	0.20	0.12	0.21	0.11	−0.14	−0.25	−0.36	−0.81	−1.12
		(2.89)	(2.76)	(1.48)	(0.92)	(1.76)	(1.27)	(−1.07)	(−1.96)	(−2.10)	(−3.89)	(−4.46)
FFC	α	0.33	0.35	0.17	0.10	0.17	0.09	−0.13	−0.23	−0.32	−0.70	−1.02
		(2.95)	(2.62)	(1.16)	(0.75)	(1.47)	(1.02)	(−0.87)	(−1.85)	(−1.74)	(−3.23)	(−3.85)
Q	α	0.25	0.24	0.08	0.00	0.09	0.08	−0.11	−0.12	−0.17	−0.41	−0.66
		(2.04)	(1.83)	(0.61)	(0.04)	(0.80)	(0.97)	(−0.76)	(−0.90)	(−1.12)	(−1.91)	(−2.79)
FF5	α	0.18	0.22	0.06	−0.01	0.09	0.06	−0.09	−0.08	−0.12	−0.32	−0.50
		(1.25)	(1.78)	(0.56)	(−0.08)	(0.91)	(0.72)	(−0.63)	(−0.71)	(−0.89)	(−1.99)	(−2.37)
	β_{MKT}	1.03	0.96	0.93	0.96	0.94	0.96	1.04	1.00	1.15	1.26	0.23
		(21.84)	(21.22)	(40.38)	(22.82)	(39.64)	(36.54)	(23.24)	(25.17)	(20.03)	(15.01)	(2.09)
	β_{SMB_5}	−0.11	−0.19	−0.16	−0.16	−0.03	0.05	−0.10	−0.02	0.00	0.13	0.24
		(−1.35)	(−3.33)	(−4.09)	(−3.35)	(−0.59)	(1.00)	(−2.08)	(−0.33)	(0.04)	(1.10)	(1.35)
	β_{HML}	0.08	0.04	0.08	0.06	−0.03	−0.03	−0.11	−0.06	0.01	−0.10	−0.18
		(0.76)	(0.45)	(0.95)	(0.80)	(−0.49)	(−0.51)	(−2.16)	(−0.72)	(0.07)	(−0.58)	(−0.76)
	β_{RMW}	0.11	0.15	0.21	0.18	0.19	0.13	−0.01	−0.24	−0.29	−0.73	−0.84
		(0.61)	(1.78)	(3.50)	(2.24)	(3.30)	(2.95)	(−0.22)	(−1.91)	(−2.02)	(−4.64)	(−2.67)
	β_{CMA}	0.34	0.29	0.20	0.19	0.15	−0.05	−0.17	−0.24	−0.47	−0.66	−1.00
		(1.48)	(2.44)	(2.08)	(2.03)	(2.15)	(−0.74)	(−1.26)	(−1.37)	(−3.08)	(−3.03)	(−2.54)
Pre-Formation	β^{BEAR}	−0.52	−0.27	−0.17	−0.09	−0.01	0.06	0.14	0.24	0.38	0.69	1.21
Post-Formation	β^{BEAR}	−0.03	−0.05	−0.05	−0.04	−0.03	−0.05	−0.00	0.01	0.16	0.19	0.21
		(−1.10)	(−2.18)	(−2.11)	(−1.64)	(−1.44)	(−3.93)	(−0.04)	(0.49)	(3.10)	(3.40)	(2.73)

Table 6: $\beta^{\mathbf{BEAR}}$-Sorted Portfolio Average Risk Variables

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

Panel A: All Stocks Sample

Variable	β^{BEAR} 1	β^{BEAR} 2	β^{BEAR} 3	β^{BEAR} 4	β^{BEAR} 5	β^{BEAR} 6	β^{BEAR} 7	β^{BEAR} 8	β^{BEAR} 9	β^{BEAR} 10
β^{CAPM}	0.77	0.76	0.75	0.75	0.77	0.81	0.86	0.93	1.01	1.14
β^{-}	0.96	0.87	0.84	0.82	0.83	0.86	0.90	0.96	1.03	1.13
$\beta^{-} - \beta^{\text{CAPM}}$	0.19	0.12	0.09	0.07	0.06	0.05	0.04	0.03	0.02	−0.01
$\beta^{\Delta\text{VIX}}$	−0.04	−0.01	−0.01	0.01	0.01	0.02	0.03	0.05	0.07	0.11
β^{VOL}	−0.05	−0.02	−0.01	−0.00	0.00	0.02	0.02	0.03	0.04	0.08
β^{JUMP}	−0.05	−0.03	−0.02	−0.01	−0.01	−0.00	−0.00	0.00	0.01	0.03
COSKEW	−1.89	−1.39	−1.17	−1.02	−0.82	−0.76	−0.69	−0.63	−0.46	−0.12
$\beta^{\Delta\text{SKEW}}$	0.08	0.06	0.10	−0.08	−0.08	−0.15	−0.05	−0.10	−0.03	−0.35
β^{TAIL}	0.31	0.27	0.25	0.23	0.23	0.23	0.23	0.24	0.25	0.25
IVOL	3.76	3.17	2.91	2.80	2.77	2.84	2.97	3.14	3.40	4.00

Panel B: Liquid Sample

Variable	β^{BEAR} 1	β^{BEAR} 2	β^{BEAR} 3	β^{BEAR} 4	β^{BEAR} 5	β^{BEAR} 6	β^{BEAR} 7	β^{BEAR} 8	β^{BEAR} 9	β^{BEAR} 10
β^{CAPM}	1.08	1.00	0.98	0.97	0.99	1.03	1.08	1.16	1.26	1.45
β^{-}	1.18	1.05	1.02	1.00	1.01	1.04	1.08	1.16	1.25	1.40
$\beta^{-} - \beta^{\text{CAPM}}$	0.10	0.06	0.04	0.03	0.02	0.01	0.01	0.00	−0.01	−0.05
$\beta^{\Delta\text{VIX}}$	−0.02	−0.00	−0.00	0.00	0.01	0.02	0.03	0.05	0.08	0.13
β^{VOL}	−0.03	−0.01	−0.01	0.00	0.01	0.01	0.02	0.03	0.04	0.07
β^{JUMP}	−0.03	−0.02	−0.01	−0.01	−0.00	−0.00	0.00	0.01	0.01	0.03
COSKEW	−0.67	−0.30	−0.28	−0.27	−0.09	−0.08	0.04	0.15	0.36	0.91
$\beta^{\Delta\text{SKEW}}$	0.15	−0.09	−0.00	−0.08	−0.15	−0.10	−0.04	−0.11	−0.13	−0.15
β^{TAIL}	0.15	0.14	0.13	0.14	0.13	0.14	0.14	0.15	0.15	0.14
IVOL	2.39	2.02	1.93	1.88	1.92	2.00	2.11	2.29	2.53	3.01

Table 6: $\beta^{\mathbf{BEAR}}$-Sorted Portfolio Average Risk Variables - continued

Panel C: Large Cap Sample

Variable	β^{BEAR} 1	β^{BEAR} 2	β^{BEAR} 3	β^{BEAR} 4	β^{BEAR} 5	β^{BEAR} 6	β^{BEAR} 7	β^{BEAR} 8	β^{BEAR} 9	β^{BEAR} 10
β^{CAPM}	1.02	0.93	0.91	0.91	0.93	0.95	0.99	1.06	1.18	1.39
β^{-}	1.11	0.98	0.95	0.94	0.95	0.96	1.00	1.06	1.16	1.35
$\beta^{-} - \beta^{\text{CAPM}}$	0.09	0.04	0.03	0.03	0.02	0.01	0.00	−0.00	−0.01	−0.04
$\beta^{\Delta\text{VIX}}$	−0.03	−0.02	−0.01	−0.01	0.00	0.00	0.01	0.04	0.06	0.11
β^{VOL}	−0.03	−0.01	−0.01	−0.00	0.00	0.01	0.01	0.02	0.03	0.06
β^{JUMP}	−0.02	−0.01	−0.01	−0.00	−0.00	0.00	0.00	0.01	0.01	0.03
COSKEW	−0.23	−0.03	−0.06	−0.04	0.01	0.24	0.35	0.46	0.63	1.32
$\beta^{\Delta\text{SKEW}}$	0.01	−0.21	−0.22	−0.16	−0.18	−0.18	−0.13	−0.07	−0.10	−0.27
β^{TAIL}	0.09	0.09	0.10	0.10	0.10	0.11	0.10	0.10	0.10	0.08
IVOL	1.96	1.66	1.59	1.56	1.59	1.62	1.71	1.83	2.05	2.48

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

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^{-}, $\beta^{-} - \beta^{\text{CAPM}}$, $\beta^{\Delta\text{VIX}}$, β^{VOL}, β^{JUMP}, COSKEW, $\beta^{\Delta\text{SKEW}}$, β^{TAIL}, or IVOL. Each month t, all stocks in the sample are sorted into decile groups based on an ascending sort on the control variable. Within each control variable group, the stocks are sorted into decile portfolios based on an ascending sort on β^{BEAR}. The monthly value-weighted excess returns for each of the resulting 100 portfolios are calculated. Within each β^{BEAR} decile, we then calculate the equal-weighted average of the portfolio excess returns across the deciles of the control variable, which we refer to as the bivariate β^{BEAR} decile portfolios. The β^{BEAR} $10-1$ portfolio is a zero-investment portfolio that is long the bivariate β^{BEAR} decile 10 portfolio and short the bivariate β^{BEAR} decile one portfolio. The table presents the time-series averages of the month $t+1$ excess returns for the bivariate β^{BEAR} decile portfolios. For the β^{BEAR} $10-1$ portfolios, the table shows the time-series averages of the month $t+1$ excess returns, alphas (α) relative to the 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 12 lags are presented in parentheses. 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 $\beta^{\Delta\text{SKEW}}$ 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). Panels A, B, and C present results for the All Stocks, Liquid, and Large Cap samples, respectively.

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

Panel A: All Stocks Sample

	Model	Value	β^{CAPM} Avg.	β^{-} Avg.	$\beta^{-}-\beta^{\mathrm{CAPM}}$ Avg.	$\beta^{\Delta\mathrm{VIX}}$ Avg.	β^{VOL} Avg.	β^{JUMP} Avg.	COSKEW Avg.	$\beta^{\Delta\mathrm{SKEW}}$ Avg.	β^{TAIL} Avg.	IVOL Avg.
β^{BEAR} 1	Excess Return	Excess Return	0.82	0.84	0.89	0.95	0.93	0.87	1.10	1.13	1.00	0.89
β^{BEAR} 2			0.65	0.75	0.84	0.87	0.73	0.82	0.80	0.53	0.88	0.76
β^{BEAR} 3			0.58	0.63	0.67	0.61	0.73	0.57	0.79	0.69	0.65	0.51
β^{BEAR} 4			0.63	0.47	0.69	0.64	0.53	0.60	0.67	0.46	0.57	0.44
β^{BEAR} 5			0.70	0.67	0.52	0.49	0.43	0.44	0.63	0.38	0.75	0.62
β^{BEAR} 6			0.49	0.57	0.49	0.65	0.75	0.49	0.77	0.64	0.61	0.61
β^{BEAR} 7			0.66	0.74	0.73	0.52	0.56	0.49	0.51	0.59	0.62	0.61
β^{BEAR} 8			0.44	0.41	0.47	0.47	0.23	0.45	0.46	0.30	0.55	0.55
β^{BEAR} 9			0.53	0.52	0.47	0.44	0.36	0.19	0.51	0.18	0.51	0.29
β^{BEAR} 10			0.15	0.17	−0.05	−0.09	−0.25	−0.14	0.01	−0.50	0.17	−0.01
β^{BEAR} 10 − 1	Excess Return	Excess Returns	−0.67	−0.67	−0.94	−1.05	−1.18	−1.00	−1.08	−1.63	−0.83	−0.90
			(−3.27)	(−3.25)	(−2.31)	(−2.35)	(−2.50)	(−2.61)	(−2.83)	(−2.44)	(−2.65)	(−2.25)
	CAPM	α	−0.78	−0.82	−1.24	−1.36	−1.44	−1.24	−1.36	−1.96	−1.10	−1.14
			(−3.95)	(−4.11)	(−3.02)	(−3.10)	(−3.02)	(−3.14)	(−3.81)	(−3.29)	(−3.91)	(−2.98)
	FF3	α	−0.73	−0.78	−1.10	−1.23	−1.29	−1.14	−1.24	−1.28	−1.02	−1.05
			(−2.92)	(−3.74)	(−4.16)	(−4.00)	(−4.66)	(−4.21)	(−4.61)	(−2.71)	(−4.15)	(−3.56)
	FFC	α	−0.77	−0.75	−1.02	−1.19	−1.24	−1.13	−1.18	−1.38	−0.92	−0.99
			(−2.97)	(−3.11)	(−3.43)	(−3.49)	(−4.27)	(−3.90)	(−3.82)	(−2.56)	(−3.52)	(−3.00)
	Q	α	−0.53	−0.54	−0.69	−0.78	−0.85	−0.69	−0.84	−1.15	−0.67	−0.73
			(−2.18)	(−2.35)	(−2.79)	(−2.42)	(−3.08)	(−2.44)	(−2.92)	(−2.27)	(−2.81)	(−2.54)
	FF5	α	−0.54	−0.57	−0.64	−0.69	−0.73	−0.57	−0.81	−0.87	−0.60	−0.67
			(−2.29)	(−2.53)	(−2.77)	(−2.86)	(−3.09)	(−1.87)	(−3.14)	(−2.27)	(−2.49)	(−2.63)
		β_{MKT}	−0.05	0.04	0.17	0.15	0.19	0.11	0.13	−0.01	0.18	0.17
			(−0.68)	(0.60)	(2.00)	(1.40)	(1.87)	(1.04)	(1.17)	(−0.05)	(2.06)	(1.85)
		β_{SMB_5}	0.48	0.47	0.29	0.32	0.25	0.44	0.39	0.27	0.32	0.16
			(3.49)	(5.00)	(2.20)	(2.21)	(1.71)	(3.21)	(2.65)	(1.59)	(2.93)	(1.35)
		β_{HML}	−0.34	−0.21	−0.26	−0.20	−0.28	−0.24	−0.32	−0.65	−0.07	−0.06
			(−1.92)	(−1.19)	(−1.10)	(−0.84)	(−1.03)	(−0.92)	(−1.23)	(−2.68)	(−0.27)	(−0.28)
		β_{RMW}	−0.32	−0.24	−0.64	−0.74	−0.64	−0.64	−0.57	−0.52	−0.49	−0.51
			(−1.60)	(−1.36)	(−2.21)	(−2.50)	(−1.96)	(−2.09)	(−1.97)	(−1.73)	(−2.03)	(−2.07)
		β_{CMA}	−0.22	−0.44	−0.75	−0.86	−0.84	−0.88	−0.70	−0.89	−0.82	−0.66
			(−0.92)	(−1.61)	(−2.22)	(−2.21)	(−2.34)	(−2.27)	(−1.68)	(−1.75)	(−2.52)	(−2.14)

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

Panel B: Liquid Sample

	Model	Value	β^{CAPM} Avg.	β^{-} Avg.	$\beta^{-}-\beta^{\text{CAPM}}$ Avg.	$\beta^{\Delta\text{VIX}}$ Avg.	β^{VOL} Avg.	β^{JUMP} Avg.	COSKEW Avg.	$\beta^{\Delta\text{SKEW}}$ Avg.	β^{TAIL} Avg.	IVOL Avg.
β^{BEAR} 1	Excess Return	Excess Return	0.80	0.82	0.89	0.89	0.85	0.88	0.94	1.00	0.96	0.91
β^{BEAR} 2			0.60	0.54	0.86	0.87	0.69	0.72	0.86	0.80	0.87	0.80
β^{BEAR} 3			0.63	0.59	0.69	0.57	0.77	0.67	0.81	0.56	0.52	0.70
β^{BEAR} 4			0.66	0.46	0.60	0.55	0.63	0.44	0.67	0.44	0.70	0.58
β^{BEAR} 5			0.58	0.64	0.53	0.76	0.48	0.51	0.80	0.67	0.66	0.51
β^{BEAR} 6			0.55	0.61	0.63	0.50	0.64	0.53	0.63	0.79	0.61	0.56
β^{BEAR} 7			0.43	0.58	0.62	0.56	0.57	0.47	0.45	0.36	0.67	0.64
β^{BEAR} 8			0.42	0.55	0.39	0.34	0.19	0.30	0.52	0.17	0.61	0.43
β^{BEAR} 9			0.51	0.58	0.40	0.48	0.20	0.23	0.41	0.07	0.44	0.37
β^{BEAR} 10			0.12	0.07	−0.05	−0.21	−0.34	−0.14	0.01	−0.49	0.16	0.11
β^{BEAR} $10-1$	Excess Return	Excess Returns	−0.68	−0.75	−0.94	−1.10	−1.18	−1.02	−0.93	−1.49	−0.80	−0.80
			(−3.48)	(−3.29)	(−2.36)	(−2.35)	(−2.33)	(−2.44)	(−2.45)	(−2.51)	(−2.79)	(−2.33)
	CAPM	α	−0.78	−0.92	−1.28	−1.44	−1.47	−1.28	−1.25	−1.83	−1.08	−1.02
			(−4.19)	(−4.13)	(−3.16)	(−2.95)	(−2.96)	(−2.97)	(−3.59)	(−3.32)	(−4.11)	(−2.94)
	FF3	α	−0.76	−0.90	−1.16	−1.32	−1.31	−1.17	−1.15	−1.22	−1.00	−0.94
			(−3.99)	(−4.67)	(−4.83)	(−4.10)	(−4.37)	(−4.30)	(−4.62)	(−3.15)	(−5.03)	(−3.53)
	FFC	α	−0.79	−0.90	−1.06	−1.22	−1.24	−1.16	−1.04	−1.27	−0.90	−0.92
			(−3.65)	(−3.94)	(−3.92)	(−3.37)	(−3.85)	(−4.01)	(−3.63)	(−2.91)	(−3.82)	(−3.01)
	Q	α	−0.70	−0.81	−0.75	−0.88	−0.91	−0.75	−0.76	−1.12	−0.65	−0.70
			(−3.21)	(−3.52)	(−3.40)	(−2.87)	(−3.44)	(−2.96)	(−2.97)	(−2.50)	(−2.98)	(−2.66)
	FF5	α	−0.71	−0.79	−0.68	−0.82	−0.78	−0.60	−0.72	−0.86	−0.62	−0.64
			(−3.45)	(−4.20)	(−3.36)	(−3.64)	(−3.24)	(−2.28)	(−3.24)	(−2.38)	(−2.83)	(−2.78)
		β_{MKT}	0.06	0.15	0.25	0.23	0.27	0.15	0.25	0.10	0.25	0.17
			(1.20)	(1.92)	(2.93)	(2.36)	(2.37)	(1.69)	(2.32)	(0.59)	(2.74)	(2.62)
		β_{SMB_5}	0.38	0.42	0.32	0.35	0.29	0.44	0.35	0.30	0.23	0.15
			(4.51)	(4.49)	(2.46)	(2.18)	(1.62)	(3.88)	(2.61)	(1.90)	(2.16)	(1.29)
		β_{HML}	−0.29	−0.15	−0.15	−0.14	−0.24	−0.22	−0.15	−0.59	0.00	−0.12
			(−2.01)	(−0.82)	(−0.73)	(−0.72)	(−0.96)	(−1.05)	(−0.62)	(−2.81)	(0.01)	(−0.66)
		β_{RMW}	−0.10	−0.05	−0.61	−0.58	−0.50	−0.62	−0.52	−0.41	−0.36	−0.44
			(−0.70)	(−0.26)	(−2.10)	(−1.91)	(−1.60)	(−2.13)	(−1.91)	(−1.41)	(−1.73)	(−1.92)
		β_{CMA}	−0.03	−0.36	−0.87	−1.01	−1.01	−0.92	−0.81	−0.86	−0.89	−0.47
			(−0.14)	(−1.12)	(−2.58)	(−2.84)	(−2.60)	(−2.54)	(−2.15)	(−1.96)	(−2.67)	(−1.94)

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

Panel C: Large Cap Sample

	Model	Value	β^{CAPM} Avg.	β^{-} Avg.	$\beta^{-}-\beta^{\mathrm{CAPM}}$ Avg.	$\beta^{\Delta\mathrm{VIX}}$ Avg.	β^{VOL} Avg.	β^{JUMP} Avg.	COSKEW Avg.	$\beta^{\Delta\mathrm{SKEW}}$ Avg.	β^{TAIL} Avg.	IVOL Avg.
β^{BEAR} 1	Excess Return	Excess Return	0.73	0.75	0.88	0.79	0.82	0.80	0.86	0.84	0.87	0.86
β^{BEAR} 2			0.68	0.59	0.80	0.88	0.70	0.69	0.86	0.86	0.85	0.93
β^{BEAR} 3			0.61	0.60	0.69	0.75	0.63	0.54	0.73	0.54	0.62	0.68
β^{BEAR} 4			0.58	0.58	0.73	0.63	0.66	0.51	0.68	0.56	0.64	0.52
β^{BEAR} 5			0.59	0.64	0.46	0.60	0.65	0.52	0.68	0.64	0.67	0.65
β^{BEAR} 6			0.51	0.63	0.64	0.58	0.53	0.59	0.64	0.77	0.63	0.50
β^{BEAR} 7			0.59	0.62	0.61	0.48	0.54	0.45	0.61	0.53	0.73	0.69
β^{BEAR} 8			0.45	0.48	0.35	0.43	0.18	0.22	0.42	0.24	0.41	0.41
β^{BEAR} 9			0.51	0.52	0.42	0.35	0.17	0.23	0.42	0.18	0.38	0.30
β^{BEAR} 10			0.25	0.26	0.09	−0.06	−0.30	−0.07	0.02	−0.43	0.21	0.30
β^{BEAR} 10 − 1	Excess Return	Excess Returns	−0.47	−0.48	−0.79	−0.85	−1.11	−0.87	−0.83	−1.27	−0.66	−0.56
			(−2.42)	(−2.43)	(−1.86)	(−2.17)	(−2.29)	(−2.07)	(−2.46)	(−2.06)	(−2.17)	(−1.84)
	CAPM	α	−0.59	−0.64	−1.09	−1.15	−1.38	−1.11	−1.15	−1.61	−0.93	−0.77
			(−3.21)	(−3.43)	(−2.48)	(−2.83)	(−2.80)	(−2.45)	(−3.49)	(−2.69)	(−2.97)	(−2.46)
	FF3	α	−0.56	−0.61	−0.98	−1.03	−1.21	−0.99	−1.04	−0.99	−0.82	−0.69
			(−3.09)	(−3.87)	(−3.61)	(−4.06)	(−3.96)	(−3.29)	(−4.67)	(−2.54)	(−4.41)	(−2.95)
	FFC	α	−0.57	−0.55	−0.89	−0.95	−1.15	−1.00	−0.94	−1.11	−0.70	−0.68
			(−2.90)	(−3.28)	(−2.92)	(−3.45)	(−3.83)	(−3.26)	(−4.08)	(−2.63)	(−3.46)	(−2.57)
	Q	α	−0.50	−0.44	−0.55	−0.65	−0.85	−0.62	−0.70	−0.98	−0.48	−0.44
			(−2.48)	(−2.61)	(−2.28)	(−2.78)	(−3.43)	(−2.43)	(−3.57)	(−2.04)	(−2.73)	(−1.94)
	FF5	α	−0.52	−0.46	−0.48	−0.57	−0.72	−0.45	−0.66	−0.62	−0.45	−0.39
			(−2.64)	(−2.87)	(−2.26)	(−3.08)	(−2.80)	(−1.87)	(−3.28)	(−1.77)	(−2.70)	(−1.84)
		β_{MKT}	0.12	0.15	0.20	0.20	0.26	0.15	0.28	0.09	0.22	0.17
			(2.40)	(2.92)	(2.63)	(2.30)	(2.90)	(1.80)	(2.81)	(0.54)	(2.70)	(3.20)
		β_{SMB_5}	0.23	0.22	0.20	0.26	0.17	0.30	0.26	0.22	0.16	0.12
			(3.48)	(2.45)	(1.32)	(1.76)	(1.08)	(2.36)	(1.96)	(1.13)	(1.18)	(1.18)
		β_{HML}	−0.25	−0.07	−0.10	−0.14	−0.27	−0.21	−0.15	−0.59	−0.04	−0.15
			(−2.08)	(−0.48)	(−0.54)	(−0.76)	(−1.18)	(−1.08)	(−0.77)	(−2.57)	(−0.22)	(−0.98)
		β_{RMW}	−0.12	−0.16	−0.70	−0.57	−0.54	−0.62	−0.44	−0.49	−0.33	−0.43
			(−0.89)	(−1.13)	(−2.47)	(−2.05)	(−1.81)	(−2.16)	(−1.74)	(−1.46)	(−1.57)	(−2.04)
		β_{CMA}	0.04	−0.34	−0.77	−0.84	−0.80	−0.81	−0.76	−0.79	−0.91	−0.44
			(0.25)	(−1.64)	(−2.71)	(−2.49)	(−2.60)	(−2.63)	(−2.40)	(−1.71)	(−2.77)	(−2.00)

Table 8: Fama and MacBeth Regression Analyses

The table below presents the results of Fama and MacBeth (1973) regressions of month $t+1$ excess stock returns on month t β^{BEAR} and control variables. The table presents the time-series averages of the monthly cross-sectional regression coefficients. t-statistics, adjusted following Newey and West (1987) using 12 lags, are presented in parentheses. Also reported are the average adjusted R-squared (Adj. R^2) and the average number of observations (n). All independent variables are winsorized at the 0.5% and 99.5% level on a monthly basis. Each column presents results for a different regression specification. The specification that includes β^{JUMP} and β^{VOL} covers the 184 months t (return months $t+1$) from December 1996 (January 1997) through March 2012 (April 2012). The specification that includes $\beta^{\Delta\text{SKEW}}$ 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)	(11)
β^{BEAR}	−0.45	−0.35	−0.36	−0.36	−0.43	−0.41	−0.35	−0.40	−0.33	−0.38	−0.29
	(−2.40)	(−2.36)	(−2.52)	(−2.46)	(−2.70)	(−2.93)	(−1.75)	(−3.06)	(−2.69)	(−3.62)	(−2.84)
β^{CAPM}		−0.15	−0.09	−0.15	−0.09	−0.14	−0.24	−0.12	−0.13	−0.05	0.31
		(−0.57)	(−0.39)	(−0.58)	(−0.27)	(−0.55)	(−0.58)	(−0.46)	(−0.53)	(−0.20)	(1.28)
β^{-}			−0.08							−0.06	−0.09
			(−0.46)							(−0.58)	(−0.93)
$\beta^{\Delta\text{VIX}}$				−0.02						−0.06	−0.04
				(−0.36)						(−1.98)	(−1.16)
β^{JUMP}					0.50						
					(0.83)						
β^{VOL}					0.32						
					(1.46)						
COSKEW						−0.01				−0.01	−0.00
						(−1.00)				(−0.80)	(−0.01)
$\beta^{\Delta\text{SKEW}}$							−0.00				
							(−0.28)				
β^{TAIL}								0.11		0.19	0.17
								(0.77)		(1.56)	(1.70)
IVOL									−0.14	−0.12	−0.08
									(−1.93)	(−1.76)	(−1.75)
SIZE											−0.18
											(−2.94)
BM											0.08
											(0.85)
MOM											−0.00
											(−0.31)
ILLIQ											0.00
											(5.51)
Y											0.31
											(2.49)
INV											0.29
											(1.35)
Intercept	0.85	0.97	0.99	0.97	0.88	1.03	1.04	0.99	1.25	1.21	1.79
	(1.94)	(2.35)	(2.44)	(2.36)	(1.81)	(2.50)	(2.12)	(2.44)	(3.45)	(3.31)	(3.13)
Adj. R^2	0.60%	2.23%	2.45%	2.36%	2.72%	2.33%	2.70%	2.54%	3.68%	4.25%	6.16%
n	4779	4779	4779	4778	5053	4363	5459	4074	4778	4065	3095

Table 8: Fama and MacBeth Regression Analyses - continued

Panel B: Liquid Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
β^{BEAR}	−0.67	−0.50	−0.49	−0.50	−0.50	−0.53	−0.58	−0.46	−0.46	−0.40	−0.29
	(−2.68)	(−3.11)	(−3.06)	(−3.24)	(−3.13)	(−3.23)	(−3.00)	(−3.14)	(−3.04)	(−2.78)	(−2.28)
β^{CAPM}		0.07	0.18	0.09	0.20	0.10	0.08	0.05	0.17	0.20	0.08
		(0.16)	(0.46)	(0.22)	(0.42)	(0.26)	(0.13)	(0.14)	(0.48)	(0.57)	(0.26)
β^{-}			−0.16							−0.11	−0.13
			(−0.71)							(−0.56)	(−0.72)
$\beta^{\Delta\mathrm{VIX}}$				−0.10						−0.12	−0.05
				(−1.38)						(−1.85)	(−0.81)
β^{JUMP}					0.13						
					(0.11)						
β^{VOL}					0.14						
					(0.54)						
COSKEW						−0.00				0.00	0.00
						(−0.36)				(0.06)	(0.60)
$\beta^{\Delta\mathrm{SKEW}}$							0.01				
							(0.66)				
β^{TAIL}								0.11		0.10	0.19
								(0.90)		(0.92)	(1.83)
IVOL									−0.16	−0.13	−0.05
									(−2.11)	(−1.71)	(−0.81)
SIZE											−0.13
											(−1.93)
BM											0.01
											(0.11)
MOM											−0.00
											(−0.02)
ILLIQ											0.21
											(1.22)
Y											0.34
											(2.35)
INV											0.05
											(0.28)
Intercept	0.72	0.70	0.75	0.69	0.53	0.72	0.63	0.75	0.86	0.91	1.59
	(1.93)	(2.05)	(2.32)	(2.08)	(1.38)	(2.24)	(1.38)	(2.33)	(2.28)	(2.66)	(2.32)
Adj. R^2	1.37%	4.94%	5.43%	5.30%	6.14%	5.19%	6.05%	5.33%	5.93%	7.19%	10.15%
n	2040	2040	2040	2040	2107	1917	2234	1824	2040	1823	1527

Table 8: Fama and MacBeth Regression Analyses - continued

Panel C: Large Cap Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
β^{BEAR}	−0.80	−0.63	−0.64	−0.61	−0.65	−0.64	−0.87	−0.53	−0.56	−0.48	−0.41
	(−2.82)	(−3.03)	(−3.11)	(−3.09)	(−3.84)	(−2.86)	(−3.46)	(−2.65)	(−2.81)	(−2.37)	(−2.30)
β^{CAPM}		0.11	0.32	0.13	0.26	0.12	0.27	0.08	0.16	0.25	0.35
		(0.25)	(0.74)	(0.31)	(0.53)	(0.28)	(0.45)	(0.19)	(0.43)	(0.66)	(0.95)
β^{-}			−0.25							−0.16	−0.33
			(−1.13)							(−0.69)	(−1.26)
$\beta^{\Delta\text{VIX}}$				−0.07						−0.09	−0.06
				(−0.71)						(−0.89)	(−0.54)
β^{JUMP}					−0.34						
					(−0.20)						
β^{VOL}					0.28						
					(0.89)						
COSKEW						−0.01				−0.01	−0.01
						(−0.94)				(−0.95)	(−0.60)
$\beta^{\Delta\text{SKEW}}$							0.01				
							(0.76)				
β^{TAIL}								0.10		0.10	0.15
								(0.61)		(0.66)	(1.25)
IVOL									−0.09	−0.05	−0.07
									(−1.15)	(−0.77)	(−1.35)
SIZE											−0.13
											(−2.08)
BM											0.02
											(0.23)
MOM											0.00
											(0.42)
ILLIQ											0.01
											(0.12)
Y											0.38
											(1.38)
INV											0.05
											(0.28)
Intercept	0.68	0.62	0.67	0.61	0.39	0.64	0.39	0.68	0.73	0.73	1.66
	(1.91)	(1.90)	(2.13)	(1.85)	(1.09)	(2.05)	(0.86)	(2.23)	(2.01)	(2.23)	(2.83)
Adj. R^2	2.12%	7.14%	7.84%	7.66%	9.00%	7.38%	8.93%	7.56%	8.01%	9.68%	13.51%
n	1005	1005	1005	1005	1023	963	1073	932	1005	932	767

Table 9: 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 excess stock returns and β^{BEAR} and control variables. Each month t we run a cross-sectional regression of month $t+k$ excess stock returns on β^{BEAR} and combinations of the control variables, for $k \in 2, 3, 4, 5, 6$. The table presents the time-series averages of the monthly cross-sectional regression coefficients on β^{BEAR}. t-statistics, adjusted following Newey and West (1987) using 12 lags, testing the null hypothesis that the average coefficient is equal to zero, are presented in parentheses. Each column presents results for a different regression specification. The specifications used in columns (1)-(11) correspond to the specifications used in the corresponding columns of Table 8. All independent variables are winsorized at the 0.5% and 99.5% level on a monthly basis. The row labeled R_{t+k} presents results using the k-month-ahead excess stock return as the dependent variable. The specification that includes β^{JUMP} and β^{VOL} covers the 184 months t from December 1996 through March 2012. The specification that includes $\beta^{\Delta\text{SKEW}}$ 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)	(11)
R_{t+2}	−0.54	−0.46	−0.48	−0.47	−0.61	−0.57	−0.50	−0.53	−0.40	−0.47	−0.35
	(−2.94)	(−3.13)	(−3.34)	(−3.15)	(−3.67)	(−3.96)	(−2.90)	(−4.08)	(−3.28)	(−4.32)	(−3.64)
R_{t+3}	−0.59	−0.52	−0.53	−0.51	−0.68	−0.63	−0.61	−0.61	−0.45	−0.55	−0.39
	(−3.23)	(−3.75)	(−3.92)	(−3.76)	(−4.27)	(−4.71)	(−3.88)	(−4.84)	(−4.04)	(−5.14)	(−4.57)
R_{t+4}	−0.62	−0.53	−0.54	−0.53	−0.62	−0.62	−0.57	−0.62	−0.46	−0.54	−0.38
	(−3.26)	(−3.65)	(−3.75)	(−3.66)	(−3.48)	(−4.36)	(−3.36)	(−4.42)	(−3.94)	(−4.46)	(−3.42)
R_{t+5}	−0.58	−0.50	−0.52	−0.50	−0.59	−0.58	−0.52	−0.58	−0.44	−0.53	−0.38
	(−3.05)	(−3.17)	(−3.29)	(−3.14)	(−2.92)	(−3.74)	(−2.97)	(−3.83)	(−3.51)	(−4.22)	(−3.42)
R_{t+6}	−0.58	−0.51	−0.52	−0.51	−0.61	−0.56	−0.66	−0.56	−0.45	−0.50	−0.36
	(−2.79)	(−2.95)	(−3.15)	(−3.00)	(−2.71)	(−3.54)	(−3.16)	(−3.48)	(−3.29)	(−4.08)	(−3.47)

Panel B: Liquid Sample

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
R_{t+2}	−0.75	−0.58	−0.61	−0.58	−0.68	−0.63	−0.68	−0.56	−0.52	−0.54	−0.41
	(−2.93)	(−3.37)	(−3.40)	(−3.38)	(−3.59)	(−3.56)	(−3.78)	(−3.43)	(−3.27)	(−3.31)	(−2.95)
R_{t+3}	−0.73	−0.54	−0.57	−0.53	−0.69	−0.58	−0.69	−0.52	−0.45	−0.50	−0.42
	(−2.68)	(−3.50)	(−3.42)	(−3.43)	(−3.67)	(−3.69)	(−4.55)	(−3.44)	(−3.20)	(−2.93)	(−3.00)
R_{t+4}	−0.73	−0.54	−0.55	−0.53	−0.62	−0.55	−0.63	−0.50	−0.48	−0.46	−0.28
	(−2.65)	(−3.15)	(−3.04)	(−3.17)	(−3.15)	(−3.22)	(−3.65)	(−3.01)	(−3.08)	(−2.64)	(−1.82)
R_{t+5}	−0.64	−0.45	−0.46	−0.45	−0.50	−0.46	−0.54	−0.41	−0.39	−0.38	−0.25
	(−2.46)	(−2.71)	(−2.78)	(−2.79)	(−2.36)	(−2.90)	(−3.04)	(−2.65)	(−2.64)	(−2.53)	(−1.83)
R_{t+6}	−0.67	−0.47	−0.48	−0.47	−0.55	−0.45	−0.71	−0.39	−0.43	−0.39	−0.27
	(−2.40)	(−2.63)	(−2.84)	(−2.84)	(−2.22)	(−2.71)	(−2.74)	(−2.32)	(−2.63)	(−2.74)	(−2.08)

Panel C: Large Cap Sample

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
R_{t+2}	−0.88	−0.72	−0.72	−0.70	−0.82	−0.74	−0.81	−0.68	−0.63	−0.61	−0.48
	(−2.86)	(−3.12)	(−3.10)	(−3.15)	(−4.06)	(−3.08)	(−3.18)	(−2.93)	(−2.86)	(−2.73)	(−2.78)
R_{t+3}	−0.74	−0.59	−0.64	−0.57	−0.73	−0.61	−0.74	−0.59	−0.53	−0.57	−0.47
	(−2.51)	(−3.51)	(−3.49)	(−3.40)	(−4.59)	(−3.50)	(−4.23)	(−3.34)	(−3.21)	(−2.96)	(−3.12)
R_{t+4}	−0.65	−0.48	−0.50	−0.46	−0.61	−0.47	−0.64	−0.48	−0.44	−0.43	−0.26
	(−2.41)	(−3.08)	(−2.94)	(−3.02)	(−3.58)	(−2.84)	(−3.51)	(−2.94)	(−2.81)	(−2.38)	(−1.81)
R_{t+5}	−0.64	−0.49	−0.52	−0.49	−0.61	−0.47	−0.62	−0.45	−0.46	−0.46	−0.32
	(−2.25)	(−2.84)	(−2.76)	(−2.96)	(−3.17)	(−2.88)	(−3.25)	(−2.67)	(−2.77)	(−2.57)	(−2.24)
R_{t+6}	−0.73	−0.56	−0.55	−0.53	−0.73	−0.48	−0.72	−0.49	−0.50	−0.45	−0.42
	(−2.20)	(−2.73)	(−2.60)	(−2.98)	(−2.68)	(−2.44)	(−2.68)	(−2.29)	(−2.58)	(−2.42)	(−2.52)