Online Appendix for "Bear Beta or Speculative Beta?—Reconciling the Evidence on Downside Risk Premium."

Tong Wang

1. Ex-Ante Bear Factors

To corroborate my findings based on the IV-driven component and shed further light on the priced source of risk, we propose a modification to the bear risk factor which allows us to focus on ex-ante downside risk. Figure 2 illustrates the research design, where the upper panel is for the basic version. Instead of considering a fixed downside threshold throughout each 5-day holding period, we adjust the threshold on Day 5 such that Distance-To-Bear-Market (DTB) remains "invariant" to realized market returns. Roughly speaking, this amounts to selecting the set of options used on each trading day so that the distance between their strikes and the index level on that day remains constant. For example, one possibility is to choose the strike prices to be always 5% below the index level on each day. Under this design, changes in the index level alone do not change the A-D price, which allows us to focus on the ex-ante risk.

We also consider several refinements to this basic design. First, we use interpolation to target a constant time-to-expiration of 45 calendar days in order to avoid the time-decay effect. This can be achieved by interpolating the prices of A-D securities with one month and two months to expiration. Second, we consider DTB defined in terms of volatility measures as opposed to a fixed percentage. One choice is to follow LM and effectively set DTB to about 1.25 times the VIX on a given day. The key difference is that we reset this DTB to 1.25 times the VIX on day t+5, while LM don't. The lower panel of Figure 2 illustrates this design.

The second adjustment above is meant to allow the separation of jump risk from diffusive risk. If we define DTB as a fixed percentage below the index level, then the probability of entering a bear market could increase for two main reasons: first, the downward jump risk increases; second, the volatility of the diffusive process increases. Hence, the basic design using a fixed DTB does not distinguish between the two channels. If we are mainly concerned with the jump process, then making the DTB proportional to the diffusive volatility effectively offsets the changes in A-D security price caused by changes in diffusive volatility.

One concern with using VIX to adjust DTB is that VIX is not only driven by the diffusive volatility, but also by variance risk premium and, potentially, jump risk. To address this concern, we estimate a predictive model of realized bipower variation (BV) and use the predicted value of BV (denoted by $\widehat{BV}$) to set DTB. Bipower variation is shown to be a suitable measure of diffusive volatility by **?**. The autoregressive models we use to predict BV are presented in Table 1.

Based on these considerations, we construct three versions of ex-ante bear risk factors, which differ only in their definitions of DTB. In Factor 1, the DTB on each day is approximately equal to 1.25 times VIX adjust for time-to-expiration of the put options. For example, if the time-to-expiration of the put options is 30 calendar days, then the DTB is $1.25 \cdot (VIX/100) \cdot \sqrt{30/365}$. In Factor 2, the DTB is approximately equal to 2 times the square root of the predicted value of the bipower variation during the life span of the options, i.e., $2 \cdot \sqrt{\widehat{BV}}$. we use a larger multiplier here because the average level and standard deviation of $\widehat{BV}$ is about half of those of VIX. In Factor 3, we replace the actual VIX by a constant of 15 and repeat the process used for Factor 1. It might be tempting to use the average VIX level for this constant threshold, which is about 20. But using such a high value results in too many missing observations in the factor during relatively quiet periods in the market, as some deeply out-of-the-money puts may not survive the sample filters.

Table 2 presents the correlations between the three factors and the market portfolio return. All three factors are negatively correlated with the market return, and the strongest correlation comes from the factor with constant-percentage DTB. This result is sensible because the ex-ante downside risk in this factor is heavily influenced by the volatility of the diffusive process, which is well-known to be strongly negatively correlated with the market return. The weakest correlation comes from the factor using VIX to determine DTB. This raises the concern that making DTB proportional to VIX might offset changes in ax-ante downside associated with not only diffusive risk but also jump risk, which is undesirable. Using predicted BV to determine DTB seems to strike a balance between the above two cases, and therefore is considered a preferred approach.

Table 3 presents the returns and betas of the stock portfolios sorted on the loadings with respect to the three ex-ante risk factors. we continue to use the two-factor models to estimate betas where each option factor is paired with the market factor. The first three panels present the average portfolio returns and alphas. Panel A shows that loadings on Factor 1 do not significantly predict future stock returns. Panel B shows that the predictive power becomes somewhat stronger when we use BV instead of VIX to determine DTB, but the results are still insignificant. In particular, the magnitude of the average long-short portfolio return is only 8 basis points per month, which is far from enough to explain the bear risk premium. Panel C shows that the return spreads are much higher when DTB is a constant percentage. The progression of the three panels suggests that ex-ante jump risk is not significantly priced in the cross-section, while diffusive volatility seems to command a respectable premium. This is consistent with my findings in Table 8 in the first submission, where we show a significant alpha associated with volatility risk.

Panel B shows the formation-period betas in the two-factor models. Clearly, the long-short portfolios have high loadings on the option factor during the formation period, as they are formed on these loadings. Panel C shows the corresponding betas in the holding period. For all three factors, the loadings on the option factor become insignificant after portfolio formation, and the economic magnitudes of these loadings are very small. Because the option factors are scaled to have the same standard deviation as the market factor, the loadings on the option factors can be compared to those on the market factor. For two of the long-short portfolios, the option betas are merely 1/10 of the market betas, and the other is 2/10. This casts further doubt on the stock market risk premium associated with ex-ante disaster risk. Even for the third factor, the post-formation beta on the option factor is fairly small, which raises the question of why volatility risk is priced in the stock market. The evidence here does not seem to favor a fully rational model. The magnitudes of the premium in Panel C is large (61 bps per month). It is unclear why rational investors would pay such a high premium for an insignificant hedge of the volatility risk. we leave the further exploration of this question to future research.

Overall, Table 3 is consistent with my findings based on the IV-driven component of the bear risk factor. There is little evidence that ex-ante downside or disaster risk is priced in the cross-section of stocks.

2. Double-sorted portfolios

We sort stocks into 5 by 5 bins on one of the bear betas and the CAPM market beta independently. The value-weighted portfolio alphas and average returns are presented in Table 4 Panel A. Portfolios sorted on the full bear betas confirm the single-sorted results, and the bear risk premium is negative in all the market beta quintiles. The linear component betas also generate consistently negative premia. Interestingly, the nonlinear component generates negative premia within *Lo* β_m and *Hi* β_m quintiles, though the premia are on average close to zero for the middle three quintiles. This might seem somewhat inconsistent with the single-sorted results where the nonlinear beta does not predict stock returns, but it is important to recognize that the two extreme β_m quintiles tend to contain smaller companies, as Panel B shows. Therefore, the contribution of these two quintiles is likely small in single-sorted value-weighted portfolios. This results echos the cross-sectional regressions reported in the paper where we find some evidence suggesting loadings on the nonlinear factor negatively predict future returns.

As we show in the paper, betas with respect to the nonlinear component are associated with asymmetric market betas during the holding period. High loadings on this component predict low downside betas relative to upside betas. A potential rational explanation of the findings in the double-sorted results is that this attractive asymmetry is particularly pronounced in *Lo* β_m and *Hi* β_m quintiles. To examine this possibility, we calculate the holding period upside and downside market betas of the 25 portfolios and present the results in Panel C. The panel shows that *Lo* β_m and *Hi* β_m quintiles in fact have the least attractive risk profile during the holding period. Therefore, the observed negative risk premium is unlikely a rational outcome.

Consistent with the single sorted results, the IV-driven beta and residual beta are not associated with strong premia.

3. The role of mispricing and IVOL

Liu et al. (2018) show that the BaB puzzle concentrates in highly overpriced and high IVOL stocks, and after removing stocks located both in the top IVOL quartile and top MISP quintile, the alpha of the BaB portfolio becomes insignificant. Following their method, we remove the stocks with high IVOL and MISP (Stambaugh et al. (2012)) and form portfolios sorted on $\beta_{Put,L}$ using the remaining stocks. The portfolio returns are reported in Table 5a Panel A, which shows that the puzzle remains strong in the filtered sample.

Liu et al. (2018) also show that the BaB puzzle concentrates among high MISP and high IVOL stocks. In Table 5a Panel B, we examine portfolios sorted independently on $\beta_{Put,L}$ and MISP using the same filtered sample as in Panel A. For brevity, this panel only reports the alphas of the portfolios with the one-month holding period. Although the last row of this panel shows that the H-L $\beta_{Put,L}$ portfolio formed using high MISP stocks delivers a highly negative alpha (-1.21), the second row shows that low MISP stocks can produce an even lower alpha (-1.25). So there doesn't seem to be a clear relationship between the current puzzle and MISP. Panel C reports the independent sorts using IVOL and $\beta_{Put,L}$ and shows no clear relationship between IVOL and the current puzzle.

The results for portfolios sorted on the original bear betas are presented in Table 5b and follow the same pattern.

4. Alphas under conditional CAPM

Shanken (1990) and Ferson and Schadt (1996) point out the importance of correctly modeling the variations in market betas to obtain unbiased alphas. Boguth et al. (2011) further show that if the beta of a portfolio co-varies with market volatility, then its alpha calculated using unconditional CAPM is biased. The authors provide a framework to decompose the difference between the alphas under unconditional and conditional CAPM into a volatility-timing component and a market-timing one, where the former represents a bias, and the latter doesn't.

We adopt the framework of Boguth et al. (2011) to analyze the potential bias in the alpha of the long-short portfolio sorted on $\beta_{Put,L}$. In doing so, we also borrow several key empirical settings suggested by Cederburg and O'Doherty (2016). At the end of each calendar quarter, stocks are sorted into deciles by their $\beta_{Put,L}$'s calculated over the prior 12 months. To calculate holding period returns, we skip a quarter and hold the value-weighted portfolios for the following quarter. The portfolio returns during the skipped quarter are used to calculate the market betas of the portfolios, which serve as the main instrument in the conditional CAPM. For example, we sort stocks into deciles at the end of Dec 2000 using $\beta_{Put,L}$ measured in the year of 2000. Then, the quarterly returns of the portfolios are measured over the second quarter of 2001. In addition, we use the daily portfolio returns in the first quarter of 2001 to calculate the market betas of the portfolios, which are used as the instruments. The conditional CAPM can be written as:

$$r_{i,t} = \alpha_i^{IV} + (\gamma_{i,0} + \gamma_{i,1}' Z_{i,t-1}) r_{m,t} + e_{i,t}, \tag{1}$$

where $r_{i,t}$ is the excess return of the testing portfolio in Quarter t, $r_{m,t}$ is the excess return of the market portfolio in Quarter t, and $Z_{i,t-1}$ is vector of the lagged instrument variables. Instruments include market betas measured in the lagged quarter (β^{IV}), log dividend yield (DY), and default spread (DS).

The estimated parameters of Equation (1) are reported in Table 6a. The results are based on the H-L portfolio sorted on $\beta_{Put,L}$. The table shows that the market beta of the portfolio is indeed time-varying and both β^{IV} and DS are significant determinants. The portfolio alpha reduces from -3.72% per quarter to about -1.90% and becomes insignificant under the conditional CAPM. The difference is mainly driven by β^{IV} and adding DY and DS don't further reduce the alpha.

To measure the bias, we decompose the difference between the two alphas into two components. The lower portion of the table reports the key statistics used to perform the decomposition: The average market excess return, $\overline{r_m}$, is 1.8% per quarter; the standard deviation of the market return, $\hat{\sigma}_m$, is 8.58% per quarter; the covariance between the market return and the instrument is -1.76, and the covariance between the market return squared and the instrument is 2.75. Boguth et al. (2011) show that the market timing component of difference is equal to $(1 + \frac{\overline{r_m}^2}{\hat{\sigma}_m^2})Cov(r_m, \beta^{IV})$ and the volatility timing component is $-\frac{\overline{r_m}}{\hat{\sigma}_m^2} Cov(r_m^2, \beta^{IV})$. Our calculations show that the market timing component is -1.83% per quarter and the volatility timing component is only -0.07%. Therefore, most of the difference between the unconditional alpha and the conditional one is driven by market timing. Intuitively, the long-short portfolio sorted on put betas happens to be more heavily loaded on the market factor before the market returns are low. While this provides an interesting characterization of the abnormal return of the portfolio, it does not imply that the abnormal return is a bias. The small volatility-timing component may seem surprising given that the linear component of put returns introduces a volatility-dependent beta. But it is also important to note that the dependence here is on implied volatility, while the volatility-timing component in Boguth et al. (2011) is about realized volatility, and the two are not always the same.

The results for portfolios sorted on the original bear betas are presented in Table 6b and they follow the same pattern.

5. Sub-sample analysis

To investigate whether our results depend on stock characteristics, we repeat our analysis within each size and liquidity tercile. At the end of each month, stocks are sorted into terciles by their market capitalization or Amihud (2002) illiquidity measures. Then, we perform the portfolio analysis within each tercile, following the same procedure as before. The results are presented in Table 7a. For brevity, only the one-month returns on the H-L portfolios are included. The first two rows in Panel A show that the predictability of β_{Put} is stronger among large stocks. The average return and the alpha are both insignificant in the tercile of small stocks. The next two rows help explain the pattern in the first two. Betas with respect to the IV-driven component, $\beta_{Put,IV}$, in fact positively predict the returns of small stocks, hence reducing the predictive power of put betas. The fifth and sixth rows show that $\beta_{Put,L}$ has significant predictive power across all the size groups. The last two rows show that $\beta_{Put,L}$ has no predictive power in any group. The patterns in Panel B are similar to those in Panel A.

The results for portfolios sorted on bear betas are in Table 7b and follow the sample pattern.

6. Control Variables in the Cross-Sectional Regressions

The cross-sectional regressions in Table 9 of the main paper include a battery of control variables. We discuss their definitions and sample periods here. As the main predictors in this paper, the option-factor betas are available from December 1996 to December 2017. Most of our control variables are available for this period except β_{RNSkew}, β_{Tail}, and β_{Jump}. we obtained these betas from the authors of the respective papers. While these three betas are all available at the beginning of my main sample period, their sample periods all end before December 2017: β_{RNSkew} ends in December 2007; β_{Tail} ends in January 2012; β_{Jump} ends in March 2012. In the regressions that include these betas, the sample period is from December 1996 to December 2007.

CAPM betas, β_{CAPM}, are calculated by regressing excess stock returns on excess market returns using the overlapping five-day returns over the prior 12 months at the end of each month. Downside market betas, $\beta_{MarketDown}$, are calculated in a similar way by including only observations with negative excess market returns. Both betas are adjusted using the Bayesian shrinkage method. Market Capitalization, ME, and Book-To-Equity Ratio, B/E, are calculated following Fama and French (1993), where Book Equity is defined as: Shareholders' Equity+Deferred Taxes+Investment Tax Credit-Convertible Debt. Corporate Investments, INV, is the annual percentage growth in Total Assets. Operating Profitability, OP, is defined as: Gross Profit-SG&A+R&D Expenses, divided by lagged Total Assets. Lagged 12-month stock returns, $LagReturn_{12months}$, are the cumulative stock returns in the 12 months prior to the current month. Idiosyncratic volatilities and VIX betas are calculated following Ang et al. (2006). Risk-neutral skewness betas are calculated following Chang et al. (2013)'s three factor model, which includes the market factor, the volatility factor and the skewness factor. Tail risk betas are calculated following Kelly and Jiang (2014). Co-skewness betas are calculated following Harvey and Siddique (2000). Jump risk betas are calculated following Cremers et al. (2015).

7. Additional Results for Portfolios Sorted on Put Betas

Sections 8 and 9 in the paper use betas with respect to the bear risk factor and its components. The corresponding results for betas with respect to SPX put returns and especially its linear component are presented here. Other than the changes in the option-factor betas, the settings of the corresponding tables are identical. Table 8 corresponds to Table 7 in the paper. Table 9 corresponds to Table 8 in the paper. Table 10 corresponds to Table 10 in the paper. Table 11 corresponds to Table 11 in the paper. The results here all confirm the findings based on the bear-beta portfolio in the main body of the paper.

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Table 1: Predict Bipower Variation

This table reports the coefficients of time-series regressions to predict bipower variation over the following one- or two-month period, where the observations are measured at the daily frequency. For the one-month (two-month) horizon, we forcast the total bipower variation over the following 22 (44) trading days. The results for predicting one-month BV are in the first two columns, and those for two-month BV are in the last two. "Lag 1-day BV" and "Lag 1-day VIX" are the bipower variation and VIX on the trading day (t) preceding the forecast period. "Lag 5-day BV" and "Lag 5-day VIX" are the total bipower variation and average VIX over trading days t-5 to t-1. All the variables in the regressions are annualized. Newey-West t-statistics with 22 (44) lags are used to account for overlapping observations.

	One-Month BV		Two-Month BV	
	Coef	T-Stat	Coef	T-Stat
Intercept	0.00	1.28	0.01	3.25
Lag 1-day BV	0.11	3.95	0.10	3.43
Lag 1-day VIX	0.41	3.79	0.30	3.29
Lag 5-day BV	0.36	3.91	0.31	3.26
Lag 5-day VIX	-0.23	-1.48	-0.18	-1.29
Adj. R^2	0.58		0.44	

Table 2: Factor Correlations

This table reports the correlation coefficients between the three ex-ante bear risk factors and the market return (r_m). All the factor returns are overlapping 5-day returns observed at the daily frequency. The three factors differ only in the specifications of the distance-to-bear-market (DTB). For factor $r_{ExAnteBear\_VIX}$, the DTB is set to be 1.25 times the VIX level. For $r_{ExAnteBear\_\widehat{BV}}$, the DTB is 2 times the predicted value of BV. For $r_{ExAnteBear\_CONST}$, the DTB is an annualized 18.75% below the index level on each trading day.

	r_m	$r_{ExAnteBear\_VIX}$	$r_{ExAnteBear\_\widehat{BV}}$
$r_{ExAnteBear\_VIX}$	-0.054		
$r_{ExAnteBear\_\widehat{BV}}$	-0.132	0.370	
$r_{ExAnteBear\_CONST}$	-0.276	0.080	0.188

Table 3: Ex-Ante Bear-Beta Portfolios

The first three panels report the average monthly returns ($\overline{R}$) and Fama-French-Carhart four-factor alphas (α) of the value-weighted portfolios sorted on the betas with respect to each of the three ex-ante bear beta factors. Results for one-month and 12-month holding periods are presented. All the betas used to sort the portfolios are calculated using 12-month rolling windows and two-factor models where each option factor is combined with the market factor. All returns are daily observations of overlapping 5-day returns. Panel D reports the formation period betas on the two factors. The subscripts identify betas that belong to the same model. For example, $\beta_{ExAnteBear\_VIX}$ and $\beta_{ExAnteBear\_VIX}$ are the betas for the two-factor model that involves the market factor and the ax-ante bear risk factor using VIX to set the DTB. Panel E reports the corresponding holding period betas.

		1	2	3	4	5	6	7	8	9	10	H-L	T-Stat
Panel A: Portfolios sorted on $\beta_{ExAnteBear\_VIX}$													
One Month	$\overline{R}$	0.75	0.84	0.80	0.79	0.69	0.74	0.81	0.82	0.69	0.59	-0.16	-0.51
	α	-0.11	0.02	0.02	0.06	-0.03	0.02	0.02	0.08	-0.05	-0.30	-0.19	-0.59
Twelve Months	$\overline{R}$	0.77	0.77	0.71	0.75	0.74	0.80	0.75	0.75	0.90	0.96	0.19	0.97
	α	-0.05	-0.01	-0.04	0.01	-0.01	0.08	0.02	0.01	0.16	0.10	0.15	0.79
Panel B: Portfolios sorted on $\beta_{ExAnteBear\_\widehat{BV}}$													
One Month	$\overline{R}$	0.82	0.56	0.77	0.71	0.67	0.71	0.47	0.47	0.63	0.75	-0.08	-0.23
	α	0.10	-0.09	0.22	0.14	0.08	0.17	-0.14	-0.21	-0.12	-0.19	-0.30	-0.92
Twelve Months	$\overline{R}$	0.78	0.73	0.78	0.81	0.77	0.75	0.67	0.79	0.84	0.77	-0.01	-0.03
	α	-0.07	-0.01	0.07	0.12	0.07	0.03	-0.04	0.02	-0.01	-0.22	-0.15	-0.68
Panel C: Portfolios sorted on $\beta_{ExAnteBear\_CONST}$													
One Month	$\overline{R}$	1.00	1.07	1.11	1.00	0.90	0.54	0.82	0.75	0.65	0.39	-0.61	-1.60
	α	0.16	0.23	0.36	0.25	0.13	-0.28	0.05	-0.10	-0.18	-0.52	-0.68	-2.13
Twelve Months	$\overline{R}$	0.82	0.85	0.86	0.93	0.78	0.63	0.73	0.62	0.67	0.74	-0.08	-0.27
	α	-0.01	0.09	0.13	0.22	0.07	-0.06	0.05	-0.08	-0.04	-0.05	-0.05	-0.19
Panel D: Ex-Ante bear risk portfolio formation-period betas													
$\beta_{ExAnteBear\_VIX}$		-0.19	-0.11	-0.07	-0.04	-0.01	0.02	0.04	0.08	0.12	0.20	0.39	50.20
β_{Market_VIX}		1.12	1.00	0.96	0.94	0.95	0.96	0.97	1.02	1.10	1.26	0.14	2.79
$\beta_{ExAnteBear\_\widehat{BV}}$		-0.20	-0.11	-0.06	-0.02	0.01	0.04	0.07	0.11	0.16	0.26	0.46	26.73
$\beta_{Market\_\widehat{BV}}$		1.09	1.01	0.96	0.94	0.94	0.96	1.01	1.08	1.19	1.36	0.27	4.27
$\beta_{ExAnteBear\_CONST}$		-0.24	-0.14	-0.09	-0.05	-0.01	0.02	0.06	0.10	0.16	0.27	0.51	32.59
β_{Market_CONST}		0.98	0.93	0.92	0.94	0.96	0.99	1.03	1.09	1.19	1.41	0.43	5.46
Panel E: Ex-Ante bear risk portfolio holding-period betas													
$\beta_{ExAnteBear\_VIX}$		-0.02	0.00	-0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.02	1.29
β_{Market_VIX}		1.12	0.98	0.95	0.93	0.95	0.96	1.00	1.04	1.11	1.24	0.12	4.85
$\beta_{ExAnteBear\_\widehat{BV}}$		-0.01	-0.01	-0.02	0.00	0.01	0.00	0.01	0.00	0.01	0.02	0.02	1.37
$\beta_{Market\_\widehat{BV}}$		1.13	1.01	0.93	0.92	0.92	0.97	1.00	1.07	1.22	1.33	0.20	6.37
$\beta_{ExAnteBear\_CONST}$		-0.02	-0.02	-0.01	-0.01	-0.01	0.02	0.02	0.01	0.02	0.01	0.03	1.62
β_{Market_CONST}		1.05	0.98	0.94	0.93	0.93	0.98	1.03	1.07	1.14	1.33	0.27	8.34

Table 4: Double-Sorted Portfolios

	Average Excess Return							Four-Factor Alpha						
	Low β_{Bear}	2	3	4	High β_{Bear}	H-L	tstat	Low β_{Bear}	2	3	4	High β_{Bear}	H-L	tstat
Panel A: Portfolio Returns														
Full Bear Beta														
Lo β_m	0.97	0.62	0.62	0.52	0.41	-0.56	(-1.59)	0.66	0.28	0.26	0.13	-0.13	-0.79	(-2.33)
2	1.06	0.62	0.75	0.67	0.31	-0.75	(-2.36)	0.57	0.17	0.25	0.13	-0.40	-0.97	(-3.31)
3	0.93	0.65	0.68	0.56	0.77	-0.16	(-0.57)	0.34	0.05	0.01	-0.05	0.03	-0.31	(-1.14)
4	0.89	0.50	0.54	0.58	0.34	-0.56	(-2.09)	0.21	-0.19	-0.10	-0.14	-0.51	-0.72	(-2.54)
Hi β_m	0.83	0.59	0.78	0.49	0.25	-0.58	(-1.42)	0.00	-0.17	-0.16	-0.40	-0.73	-0.73	(-1.77)
Linear Index-Driven														
Lo β_m	0.79	0.71	0.66	0.69	0.47	-0.33	(-0.79)	0.46	0.39	0.26	0.29	-0.02	-0.48	(-1.32)
2	0.96	0.75	0.59	0.65	0.35	-0.61	(-1.59)	0.49	0.26	0.08	0.10	-0.34	-0.83	(-2.48)
3	0.93	0.70	0.55	0.52	0.64	-0.29	(-0.83)	0.33	0.13	-0.15	-0.14	-0.08	-0.41	(-1.56)
4	0.57	0.59	0.54	0.65	0.35	-0.21	(-0.63)	-0.20	-0.08	-0.03	-0.11	-0.54	-0.34	(-1.23)
Hi β_m	0.83	0.42	0.38	0.56	0.30	-0.53	(-1.27)	-0.04	-0.47	-0.54	-0.26	-0.67	-0.62	(-1.82)
NonLinear Index-Driven														
Lo β_m	0.95	0.84	0.89	0.60	0.40	-0.55	(-1.96)	0.56	0.47	0.54	0.26	-0.04	-0.60	(-2.11)
2	0.77	0.85	0.75	0.73	0.62	-0.14	(-0.51)	0.17	0.37	0.34	0.22	0.03	-0.14	(-0.51)
3	0.82	0.66	0.73	0.60	0.72	-0.10	(-0.40)	0.15	0.08	0.13	-0.02	0.09	-0.07	(-0.30)
4	0.37	0.60	0.82	0.46	0.63	0.25	(0.82)	-0.41	-0.07	0.15	-0.22	-0.06	0.35	(1.25)
Hi β_m	0.79	0.62	0.19	0.60	0.32	-0.47	(-1.28)	-0.16	-0.36	-0.66	-0.31	-0.50	-0.35	(-0.91)
IV-Driven														
Lo β_m	0.63	0.87	0.73	0.83	0.61	-0.02	(-0.07)	0.25	0.61	0.39	0.50	0.11	-0.13	(-0.53)
2	0.87	0.75	0.68	0.79	0.80	-0.07	(-0.27)	0.40	0.28	0.19	0.32	0.27	-0.14	(-0.52)
3	1.02	0.69	0.66	0.66	0.79	-0.24	(-1.28)	0.40	0.15	0.05	0.01	0.14	-0.27	(-1.37)
4	0.61	0.63	0.53	0.59	0.64	0.03	(0.11)	-0.08	-0.04	-0.17	-0.01	-0.13	-0.05	(-0.18)
Hi β_m	0.33	0.36	0.62	0.68	0.17	-0.17	(-0.47)	-0.54	-0.51	-0.29	-0.09	-0.87	-0.33	(-0.80)
Residual														
Lo β_m	0.63	0.77	0.80	0.82	0.79	0.16	(0.60)	0.10	0.42	0.48	0.57	0.39	0.29	(1.05)
2	0.82	0.81	0.66	0.81	0.82	0.00	(0.01)	0.28	0.32	0.17	0.34	0.35	0.08	(0.28)
3	0.72	0.66	0.76	0.63	1.06	0.34	(1.60)	0.06	0.01	0.17	0.07	0.45	0.38	(1.80)
4	0.73	0.47	0.52	0.62	0.67	-0.05	(-0.21)	-0.04	-0.18	-0.14	-0.05	-0.03	0.01	(0.04)
Hi β_m	0.12	0.59	0.69	0.54	0.29	0.17	(0.47)	-0.89	-0.18	-0.21	-0.32	-0.58	0.32	(0.78)

Panel B: Nonlinear Index-Driven, Average Size($Billions)

Lo β_m	1.23	2.41	3.88	3.69	1.65
2	2.59	6.01	6.21	5.68	3.08
3	2.67	5.39	6.29	4.74	2.68
4	2.28	4.45	5.05	4.59	3.06
Hi β_m	1.63	2.65	3.39	3.80	2.86

Panel C: Nonlinear Index-Driven, Holding-Period Upside and Downside Betas

Lo β_m	0.55	0.51	0.43	0.45	0.56	0.01	0.29	$\beta_{MarketDown}$
	0.47	0.39	0.42	0.38	0.45	-0.02	-0.63	$\beta_{MarketUp}$
2	0.75	0.71	0.63	0.69	0.77	0.02	0.34	$\beta_{MarketDown}$
	0.69	0.65	0.62	0.64	0.71	0.02	0.52	$\beta_{MarketUp}$
3	0.92	0.91	0.87	0.93	0.95	0.03	0.67	$\beta_{MarketDown}$
	0.94	0.83	0.90	0.90	0.98	0.04	1.21	$\beta_{MarketUp}$
4	1.29	1.17	1.11	1.11	1.14	-0.17	-2.97	$\beta_{MarketDown}$
	1.24	1.16	1.17	1.20	1.27	0.03	0.56	$\beta_{MarketUp}$
Hi β_m	1.51	1.59	1.61	1.57	1.60	0.10	1.21	$\beta_{MarketDown}$
	1.68	1.70	1.70	1.76	1.71	0.03	0.41	$\beta_{MarketUp}$

Table 5a: The Role of Mispricing and IVOL

This table reports the average monthly returns ($\overline{R}$) and Fama-French-Carhart four-factor alphas (α) of the value-weighted decile portfolios sorted on $\beta_{Put,L}$, the loading on the linear component of the at-the-money SPX put returns. Throughout this table, stocks that are located both in the highest IVOL tercile and the highest MISP quintile are excluded from the portfolios. Panel A is for the portfolios sorted only on $\beta_{Put,L}$, and it contains results for the one-month and 12-month holding periods. Panels B and C report double-sorted portfolio returns. Panel B is for independent 5-by-10 sorts on MISP and $\beta_{Put,L}$, and Panel C is for independent sorts on IVOL and $\beta_{Put,L}$. To save space, Panels B and C only include the four-factor alphas from the one-month holding period. Column "T-Stat" contains the Newey-West t-statistics of the H-L portfolio returns.

		1	2	3	4	5	6	7	8	9	10	H-L	T-Stat
Panel A: Removing High MISP and High IVOL Stocks													
One Month	$\overline{R}$	1.21	0.78	0.83	0.65	0.60	0.90	0.54	0.71	0.73	0.26	-0.95	-1.97
	α	0.52	0.07	0.15	-0.01	-0.06	0.15	-0.17	-0.07	-0.12	-0.68	-1.20	-3.47
Twelve Months	$\overline{R}$	1.12	0.92	0.81	0.74	0.77	0.82	0.56	0.67	0.73	0.55	-0.57	-1.40
	α	0.32	0.18	0.07	0.04	0.09	0.07	-0.17	-0.13	-0.12	-0.39	-0.71	-2.60
Panel B: Double-Sorted Portfolios on $\beta_{Put,L}$ and MISP													
Low MISP		0.47	0.36	-0.01	0.39	-0.11	-0.01	-0.19	0.16	0.47	-0.21	-0.68	-1.493
2		0.66	-0.04	0.19	0.04	0.32	0.24	0.18	-0.21	0.10	-0.59	-1.25	-2.928
3		0.54	-0.08	0.37	-0.19	-0.19	0.42	-0.24	-0.02	0.03	-0.26	-0.80	-1.723
4		0.19	0.13	0.24	0.17	-0.21	0.04	0.11	-0.15	-0.67	-0.82	-1.01	-2.293
High MISP		0.09	-0.14	-0.25	-0.26	-0.81	-0.53	-0.95	-0.25	-0.53	-1.12	-1.21	-3.039
Panel C: Double-Sorted Portfolios on $\beta_{Put,L}$ and IVOL													
Low IVOL		0.20	0.05	0.00	0.01	0.02	0.28	0.11	0.35	0.78	-0.62	-0.80	-2.07
2		0.44	0.01	0.29	-0.17	-0.01	0.03	-0.08	0.09	-0.03	-0.68	-1.13	-2.81
3		0.62	-0.11	0.25	0.14	-0.19	-0.07	-0.46	-0.26	-0.20	-0.40	-1.03	-2.39
4		0.27	0.26	0.04	0.05	0.42	0.30	-0.01	-0.27	-0.22	-0.60	-0.87	-1.96
High IVOL		0.79	0.20	0.43	0.51	-0.47	0.28	-0.79	0.01	-0.20	-0.35	-1.14	-2.07

Table 5b: The Role of Mispricing and IVOL, Bear-Beta Portfolios

		1	2	3	4	5	6	7	8	9	10	H-L	T-Stat
Panel A: Removing High MISP and High IVOL Stocks													
One Month	$\overline{R}$	1.21	1.05	0.76	0.74	0.74	0.63	0.64	0.53	0.58	0.20	-1.01	-2.27
	α	0.47	0.38	0.13	0.04	0.04	-0.10	-0.09	-0.26	-0.31	-0.73	-1.20	-3.44
Twelve Months	$\overline{R}$	1.07	0.95	0.84	0.79	0.75	0.73	0.74	0.68	0.57	0.28	-0.79	-2.27
	α	0.24	0.19	0.12	0.10	0.07	0.04	0.00	-0.11	-0.26	-0.63	-0.86	-3.31
Panel B: Double-Sorted Portfolios on β_{Bear} and MISP													
Low MISP		0.61	0.42	-0.03	0.30	0.31	0.21	-0.13	-0.23	0.07	-0.16	-0.77	-1.99
2		0.26	0.44	0.44	0.24	0.04	0.22	0.19	-0.28	-0.05	-0.54	-0.80	-2.02
3		0.54	0.27	0.19	0.04	0.02	-0.22	0.26	-0.34	-0.22	0.05	-0.49	-1.10
4		0.63	0.39	0.14	-0.31	-0.21	0.15	-0.01	0.11	-0.45	-0.81	-1.44	-3.35
High MISP		0.04	0.14	-0.44	-0.09	-0.42	-0.58	-0.90	-0.62	-0.82	-1.29	-1.33	-2.72
Panel C: Double-Sorted Portfolios on β_{Bear} and IVOL													
Low IVOL		0.56	0.44	0.17	0.00	0.08	0.33	0.18	0.02	0.12	0.02	-0.54	-1.43
2		0.43	0.01	0.17	-0.13	0.08	-0.02	0.01	-0.23	0.18	-0.48	-0.91	-2.24
3		0.72	0.01	0.05	-0.21	-0.01	-0.26	0.21	-0.53	-0.71	-0.24	-0.95	-2.37
4		0.27	0.56	0.24	0.11	-0.56	0.01	0.05	-0.05	0.00	-0.69	-0.96	-1.87
High IVOL		0.17	0.71	0.10	-0.42	0.46	-0.79	-0.05	-0.21	-0.33	-0.53	-0.70	-1.30

Table 6a: Alphas under Conditional and Unconditional CAPM

This table reports the regression coefficients of conditional CAPM and the decomposition of the difference between unconditional and conditional alpha. The dependent variable is the quarterly excess return of the H-L portfolio sorted on $\beta_{Put,L}$. The portfolios are updated at the end of each calendar quarter and held in the quarter after the following one. The portfolio returns during the skipped quarter are used to calculate the instrument variable β^{IV}. The other two instruments are the log dividend yield (DY) and the default spread (DS). At the bottom of each panel, we report the statistics needed for calculating the decomposition of the difference between the unconditional and conditional alpha, followed by the result of the decomposition. $\overline{r_m}$ is the average market excess return. $\hat{\sigma}_m$ is the standard deviation of the excess market return. $Cov(r_m, \beta^{IV})$ is the covariance between the instrument variable beta and the market return. $Cov(r_m^2, \beta^{IV})$ is the covariance between the instrument variable beta and the market return squared. The decomposition is given by the following equations: Market Timing Component $= (1 + \frac{\overline{r_m}^2}{\hat{\sigma}_m^2})Cov(r_m, \beta^{IV})$; Volatility Timing Component $= -\frac{\overline{r_m}}{\hat{\sigma}_m^2} Cov(r_m^2, \beta^{IV})$. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	[1]	[2]	[3]
α	-3.72	-1.90	-2.06
	(-2.75***)	(-1.96*)	(-2.15**)
r_m	0.85	0.25	-0.37
	(3.67***)	(1.87*)	(-0.17)
$\beta^{IV} \cdot r_m$		0.96	0.86
		(6.08***)	(4.44***)
$DY \cdot r_m$			-0.32
			(-0.58)
$DS \cdot r_m$			-53.35
			(-3.45***)
R^2	0.314	0.596	0.644

Decomposing the difference between unconditional and conditional alphas

$\overline{r_m}$	$\hat{\sigma}_m$	$Cov(r_m, \beta^{IV})$	$Cov(r_m^2, \beta^{IV})$
1.80	8.58	-1.76	2.75
Market Timing	-1.83		
Volatility Timing	-0.07		

Table 6b: Alphas under Conditional and Unconditional CAPM, Bear-Beta Portfolios

	H-L Portfolio Sorted On Bear Betas		
	[1]	[2]	[3]
α	-3.83	-1.50	-1.63
	(-3.26***)	(-1.88*)	(-2.12**)
r_m	0.74	0.08	-0.07
	(3.86***)	(0.61)	(-0.03)
$\beta^{IV} \cdot r_m$		0.95	0.90
		(5.03***)	(3.48***)
$DY \cdot r_m$			-0.15
			(-0.21)
$DS \cdot r_m$			-36.78
			(-2.48**)
R^2	0.298	0.549	0.577
Decomposing the difference between unconditional and conditional alphas			
$\overline{r_m}$	σ_m	$Cov(r_m, \beta^{IV})$	$Cov(r_m^2, \beta^{IV})$
1.80	8.58	-1.99	13.58
Market Timing	-2.08		
Volatility Timing	-0.33		

Table 7a: Portfolio Returns in Size and Liquidity Subsamples

This table presents the average returns and Fama-French-Carhart alphas of the value-weighted portfolios sorted on put betas and its three components within each size or illiquidity tercile. At the end of each month, stocks are first sorted into terciles by their market capitalizations or Amihud illiquidity measures. Then they are sorted into deciles by the option-factor betas within each tercile. The holding period is one month throughout the table. Only the returns on the high-minus-low portfolios are reported. T-statistics are calculated using Newey-West method with one lag.

Panel A: Size Terciles

H-L Portfolio Sorted On		Small		Medium		Large	
		H-L	T-Stat	H-L	T-Stat	H-L	T-Stat
β_{Put}	$\overline{R}$	-0.27	-0.82	-0.61	-1.56	-0.82	-1.68
	α	-0.36	-1.13	-0.72	-2.31	-1.07	-2.90
$\beta_{Put,IV}$	$\overline{R}$	0.58	2.43	0.14	0.52	-0.08	-0.27
	α	0.47	2.02	-0.10	-0.39	-0.16	-0.52
$\beta_{Put,L}$	$\overline{R}$	-0.81	-2.23	-0.83	-1.91	-0.87	-1.71
	α	-0.87	-2.59	-0.95	-2.86	-1.18	-3.16
$\beta_{Put,NL}$	$\overline{R}$	0.45	1.70	0.24	0.85	0.20	0.55
	α	0.33	1.34	0.27	1.16	0.27	0.89

Panel B: Amihud Illiquidity Terciles

		Illiquid		Medium		Liquid	
		H-L	T-Stat	H-L	T-Stat	H-L	T-Stat
β_{Put}	$\overline{R}$	-0.23	-0.73	-0.57	-1.39	-0.87	-1.75
	α	-0.42	-1.33	-0.63	-1.89	-1.12	-2.97
$\beta_{Put,IV}$	$\overline{R}$	0.72	2.81	0.34	1.16	0.02	0.05
	α	0.55	2.10	0.12	0.42	-0.06	-0.19
$\beta_{Put,L}$	$\overline{R}$	-0.87	-1.71	-0.83	-1.91	-0.81	-2.23
	α	-1.18	-3.16	-0.95	-2.86	-0.87	-2.59
$\beta_{Put,NL}$	$\overline{R}$	0.20	0.55	0.24	0.85	0.45	1.70
	α	0.27	0.89	0.27	1.16	0.33	1.34

Table 7b: Size and Iliquidity Subsamples, Bear-Beta Portfolios

Panel A: Size Terciles

H-L Portfolio Sorted On		Small		Medium		Large	
		H-L	T-Stat	H-L	T-Stat	H-L	T-Stat
β_{Bear}	$\overline{R}$	-0.15	-0.49	-0.48	-1.26	-0.90	-2.07
	α	-0.26	-0.80	-0.57	-1.80	-1.16	-3.40
$\beta_{Bear,IV}$	$\overline{R}$	0.40	1.79	0.07	0.28	-0.15	-0.51
	α	0.38	1.67	-0.16	-0.69	-0.30	-1.09
$\beta_{Bear,L}$	$\overline{R}$	-0.78	-2.10	-0.84	-1.95	-0.72	-1.42
	α	-0.85	-2.43	-0.96	-2.87	-1.04	-2.77
$\beta_{Bear,NL}$	$\overline{R}$	0.39	1.42	0.31	1.11	0.03	0.07
	α	0.28	1.09	0.35	1.44	0.09	0.28

Panel B: Amihud Illiquidity Terciles

		Illiquid		Medium		Liquid	
		H-L	T-Stat	H-L	T-Stat	H-L	T-Stat
β_{Bear}	$\overline{R}$	-0.36	-1.25	-0.59	-1.55	-0.87	-1.93
	α	-0.56	-1.89	-0.61	-1.89	-1.12	-3.21
$\beta_{Bear,IV}$	$\overline{R}$	0.50	2.07	0.28	1.08	-0.16	-0.55
	α	0.37	1.47	0.05	0.19	-0.29	-1.02
$\beta_{Bear,L}$	$\overline{R}$	-0.72	-1.42	-0.84	-1.95	-0.78	-2.10
	α	-1.04	-2.77	-0.96	-2.87	-0.85	-2.43
$\beta_{Bear,NL}$	$\overline{R}$	0.03	0.07	0.31	1.11	0.39	1.42
	α	0.09	0.28	0.35	1.44	0.28	1.09

Table 8: Aggregate Disagreement

Panel A: Speculative Stocks

		Coefficient	T-statistic
One Month	Intercept	0.062	1.751
	Aggregate Disagreement	-0.012	-1.713
Six Months	Intercept	0.311	2.478
	Aggregate Disagreement	-0.062	-2.558
Twelve Months	Intercept	0.451	2.540
	Aggregate Disagreement	-0.090	-2.694

Panel B: Non-Speculative Stocks

		Coefficient	T-statistic
One Month	Intercept	-0.002	-0.059
	Aggregate Disagreement	-0.002	-0.272
Six Months	Intercept	0.102	1.262
	Aggregate Disagreement	-0.030	-1.976
Twelve Months	Intercept	0.199	1.384
	Aggregate Disagreement	-0.052	-1.974

Table 9: Controlling for Ex-Ante Skewness, FMAX, and SMR factors

This table reports the coefficients of regressing the monthly excess returns of the high-minus-low portfolio sorted on $\beta_{Put,L}$ on the Fama-French factors (r_m, SMB, HML) , Carhart factor (UMD), BaB factor (BaB), ex-ante skewness factors (SK, LUSK, USK, LSK), MAX factor (FMAX), and safe-minus-risky factor (SMR). $\beta_{Put,L}$ is the loading on the linear component of the at-the-money SPX put returns. T-statistics adjusted for heteroskedasticity are in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
α	-1.23	-1.35	-1.29	-1.07	-0.81	-1.04	-0.80
	(-2.94***)	(-2.95***)	(-2.79***)	(-2.33**)	(-2.06**)	(-2.35**)	(-2.02**)
r_m	0.42	0.30	0.20	0.16	-0.02	0.24	-0.11
	(3.86***)	(2.31**)	(1.49)	(1.21)	(-0.14)	(1.82*)	(-0.86)
SMB	0.96	0.65	0.52	0.51	0.47	0.60	0.18
	(6.53***)	(3.08***)	(2.62***)	(2.69***)	(2.99***)	(3.01***)	(0.96)
HML	-0.74	-1.00	-0.86	-0.83	-0.45	-0.65	-0.55
	(-3.48***)	(-4.16***)	(-3.26***)	(-3.14***)	(-2.66***)	(-2.79***)	(-2.49**)
UMD	0.18	0.40	0.42	0.41	0.14	0.23	0.29
	(1.42)	(2.89***)	(3.01***)	(2.98***)	(1.31)	(1.79*)	(2.21**)
BaB	-0.18	0.07	0.07	0.08	0.25	-0.11	0.31
	(-1.07)	(0.42)	(0.39)	(0.45)	(1.51)	(-0.65)	(1.76*)
SK		-0.15					
		(-2.09**)					
LUSK			-0.13				
			(-2.67***)				
USK				0.18			0.07
				(0.83)			(0.35)
LSK				-0.47			-0.19
				(-2.35**)			(-0.89)
FMAX					0.77		0.60
					(5.62***)		(3.48***)
SMR						-0.37	-0.18
						(-2.47**)	(-1.12)
Adj. R^2	0.499	0.546	0.560	0.569	0.573	0.546	0.616

Table 10: Including the Three Components of Put Returns in One Model

This table reports the average returns and Fama-French-Carhart alphas of the value-weighted stock portfolios sorted on betas with respect to the three components of SPX put option returns. Stocks are sorted into deciles using each beta; only the results for the high-minus-low portfolios are reported for brevity. Stock betas are calculated following the regression model: $r_i = a_i + \beta_{m,i} \cdot r_m + \beta_{Vol,i} \cdot volatility\ factor + \beta_{Put,L,i} \cdot r_{Put,L} + \beta_{Put,NL,i} \cdot r_{Put,NL} + e_i$, where r_i is the return of stock i, r_m is the market return, and $r_{Put,L}$ and $r_{Put,NL}$ are the linear and nonlinear components of put returns. The $volatility\ factor$ is chosen to be the IV-driven component of put returns to produce the results in the first two columns and the changes in VIX to produce the last two columns. The regression models are estimated using the prior 12 months of overlapping five-day returns at the end of each month. Columns titled "H-L" are returns or alphas. Columns titled "T-Stat" are Newey-West t-statistics with one lag.

H-L Portfolio			IV-Driven Bear Factor as Vol Factor		Change In VIX as Vol Factor	
Sorted on			H-L	T-Stat	H-L	T-Stat
β_{Vol}	One Month	$\overline{R}$	-0.33	-1.06	-0.50	-1.13
		α	-0.55	-1.77	-0.85	-2.48
	Twelve Months	$\overline{R}$	0.06	0.24	-0.22	-0.64
		α	-0.06	-0.24	-0.41	-1.76
$\beta_{Put,L}$	One Month	$\overline{R}$	-0.83	-1.65	-1.10	-2.19
		α	-1.11	-3.15	-1.42	-4.02
	Twelve Months	$\overline{R}$	-0.59	-1.45	-0.70	-1.75
		α	-0.67	-2.32	-0.80	-2.91
$\beta_{Put,NL}$	One Month	$\overline{R}$	0.03	0.10	0.01	0.02
		α	0.19	0.63	0.18	0.63
	Twelve Months	$\overline{R}$	-0.04	-0.16	0.03	0.11
		α	0.04	0.21	0.13	0.61

Table 11: Cross-Sectional Regressions

This table reports the coefficients of the cross-sectional regressions of monthly stock returns on the option-factor betas and control variables using the method of Fama-MacBeth. The cross-sectional regressions are performed at a monthly frequency. The main predictors include the put beta and the betas with respect to the three components of put returns—$\beta_{Put,IV}$, $\beta_{Put,L}$, and $\beta_{Put,NL}$. The control variables include one-factor CAPM beta β_{CAPM}, market capitalization ME, book-to-equity ratio B/E, lagged 12-month stock return $LagReturn_{12months}$, idiosyncratic volatility IVOL, corporate investments INV, operating profitability OP, downside market beta $\beta_{MarketDown}$, VIX beta β_{VIX}, risk-neutral skewness beta β_{RNSkew}, co-skewness beta β_{CoSkew}, tail risk beta β_{Tail}, and jump risk beta β_{Jump}. All the independent variables are winsorized at 0.5% and 99.5% levels. T-statistics based on the Newey-West method with 12 lags are in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Predicting Returns In One Month

	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	1.17	0.84	0.63	1.22	0.86	0.66
	(3.08***)	(2.83***)	(1.41)	(3.33***)	(2.96***)	(1.52)
β_{Put}	-0.27	-0.21	-0.18			
	(-1.81*)	(-2.67***)	(-1.5)			
$\beta_{Put,IV}$				0.18	0.18	0.24
				(0.59)	(0.96)	(0.76)
$\beta_{Put,L}$				-0.22	-0.15	-0.10
				(-2.31**)	(-2.56**)	(-1.13)
$\beta_{Put,NL}$				0.03	-0.14	-0.22
				(0.13)	(-0.76)	(-0.82)
β_{CAPM}		0.12	0.07		0.11	0.04
		(0.57)	(0.37)		(0.5)	(0.17)
ME		-0.00	-0.00		-0.00	-0.00
		(-1.84*)	(-1.33)		(-2.29**)	(-1.62)
B/E		0.18	0.44		0.18	0.43
		(1.65)	(3.62***)		(1.61)	(3.48***)
$LagReturn_{12months}$		-0.13	0.31		-0.11	0.33
		(-0.45)	(1.43)		(-0.4)	(1.58)
IVOL		-0.07	-0.03		-0.07	-0.04
		(-1.35)	(-0.39)		(-1.38)	(-0.5)
Amihud Illiquidity		0.03	0.03		0.03	0.03
		(5.27***)	(3.28***)		(5.31***)	(3.31***)
INV		-0.50	-0.52		-0.49	-0.50
		(-4.5***)	(-4.19***)		(-4.36***)	(-4.01***)
OP		1.51	1.74		1.51	1.77
		(5.99***)	(3.82***)		(6.16***)	(4.03***)
$\beta_{MarketDown}$		-0.10	-0.05		-0.08	-0.02
		(-0.7)	(-0.24)		(-0.54)	(-0.12)
β_{VIX}		-0.02	-0.14		-0.03	-0.14
		(-0.65)	(-2.52**)		(-0.82)	(-2.6**)
β_{CoSkew}		-0.01	-0.02		-0.01	-0.02
		(-2.28**)	(-1.96*)		(-2.19**)	(-1.75*)
β_{RNSkew}			-1.69			-1.74
			(-2.19**)			(-2.2**)
β_{Tail}			0.30			0.31
			(1.46)			(1.54)
β_{Jump}			-0.08			-0.27
			(-0.23)			(-0.94)
R^2	0.01	0.06	0.06	0.01	0.06	0.07

Panel B: Predicting Returns In Three, Six, And 12 Months

			Three Months			
β_{Put}	-0.33	-0.23	-0.32			
	(-2.47**)	(-3.75***)	(-3.46***)			
$\beta_{Put,IV}$				0.12	0.20	-0.05
				(0.37)	(1.21)	(-0.26)
$\beta_{Put,L}$				-0.25	-0.18	-0.21
				(-2.96***)	(-3.75***)	(-3.02***)
$\beta_{Put,NL}$				-0.12	-0.17	-0.28
				(-0.5)	(-1.05)	(-1.11)
			Six Months			
β_{Put}	-0.39	-0.28	-0.29			
	(-2.68***)	(-3.92***)	(-2.38**)			

$\beta_{Put,IV}$				0.06	0.03	-0.18
				(0.23)	(0.18)	(-0.75)
$\beta_{Put,L}$				-0.25	-0.18	-0.19
				(-2.44**)	(-3.25***)	(-2.66***)
$\beta_{Put,NL}$				-0.43	-0.50	-0.40
				(-1.79*)	(-3.43***)	(-1.37)
			12 Months			
β_{Put}	-0.08	-0.03	-0.11			
	(-0.74)	(-0.52)	(-0.93)			
$\beta_{Put,IV}$				0.04	0.09	-0.18
				(0.17)	(0.53)	(-0.83)
$\beta_{Put,L}$				-0.04	-0.01	-0.05
				(-0.48)	(-0.19)	(-0.68)
$\beta_{Put,NL}$				-0.02	0.07	-0.03
				(-0.11)	(0.51)	(-0.11)