Market Right-Tail Risk Matters![*]

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Abstract

We dissect the pricing implications of both market left- and right-tail risks for the cross-section of stock returns with portfolio trading strategies that load on one risk factor but are orthogonal to the other. The resulting time series of factors estimated from daily Standard & Poors 500 index options data are forward-looking and show low correlations with other known risk factors. Stocks with high sensitivity toward innovations in market left-tail (right-tail) risk exhibit low (high) returns on average. The market right-tail risk premium is statistically and economically significant. It cannot be explained by other common risk factors or firm characteristics, and it partially absorbs the left-tail risk premium. The large effect of right-tail risk on cross-sectional stock returns stands in contrast to the previous finding that only negative jumps are priced by the market.

Keywords: tail risk; factor-mimicking portfolios; risk premiums; cross-sectional stock returns

JEL classification: G11, G12

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1. Introduction

Debates over the impact of market tail risk on stock returns never cease. To date, studies mainly focus on the time-series or cross-sectional pricing tests of downside/disaster risk, with very few centering on the pricing implications of right-tail risk. The primary reason for this is that researches usually find that left- and right-tail dynamics, estimated from realized returns distribution, are fairly symmetric, and left-tail risk dominates right-tail risk. In this paper, we provide a new method to estimate relatively high frequent right- and left-tail risks from the risk-neutral distribution. The resulting measures are thus forward-looking and exhibit low correlation between themselves and with other known risks. We then conduct a comprehensive empirical investigation into the pricing of both tail risks in the cross-section of expected stock returns, with a particular interest in testing whether they command different premiums.

Although recent research appears to agree that disaster risk is crucial for asset pricing, no consensus has been reached on the effect of right-tail risk.[1] Right-tail risk, however, potentially carries essential information about the future investment opportunity set and can command a risk premium different from that of left-tail risk.[2] Investors who seek to insure themselves against extreme events that dramatically worsen future investment opportunities will find stocks with high sensitivities to innovations in market left-tail risk attractive and thus demand lower expected returns. Conversely, we conjecture that investors may find stocks with high exposures to the uncertainty of large market gains less desirable and thus demand higher expected returns, as this type of stocks have low payoffs when investors have high marginal utility and large payoffs when investors have low marginal utility. As such, an investigation of market right-tail risk as a pricing factor in the cross-section of stock returns is warranted.

To achieve the cross-sectional pricing test of both left- and right-tail risks, we need to measure these two risks separately while controlling for other risk factors. We construct portfolio trading strategies that load on one factor but are orthogonal to the other. Specifically, our LEFT (RIGHT)

[1] See, e.g., Gabaix (2012), Wachter (2013), and Kelly and Jiang (2014), among others.

[2] Recent studies provide evidence that the right tail of return distribution contains important information and affects investor behavior and financial markets. Investors not only look at the left-tail distribution of returns to control for risk, but also consider the right-tail distributional information for opportunity. Kumar (2009), Han and Kumar (2013), and Kumar, Page, and Spalt (2016) show that individual investors are attracted to "lottery-type" stocks with low prices, high idiosyncratic volatility, and high idiosyncratic skewness. Bali, Cakici, and Whitelaw (2011) find that stocks with high daily maximum returns in the previous month underperform those with low maximum daily returns. This paper, however, investigates the right tail of aggregate market return distribution.

trading strategy involves out-of-the-money put (call) S&P 500 options, at-the-money call (put) options, and the underlying, such that the portfolios are sensitive only to the left (right) tail of risk-neutral density of market returns and have no exposure to changes in the underlying movement (Delta neutral) or volatility (Vega neutral). In contrast with historical tail (disaster) risk measures (e.g., Kelly and Jiang (2014)), our measures are obtained using a single day-of-option data and are thus forward-looking. The ex-ante tail risk perceived by investors may be quite different from the ex-post realized risk in prices because even high-probability tail risk may fail to materialize in the sample (Santa-Clara and Yan (2010)). Furthermore, our measures capture the relatively high frequent variations of tail dynamics. Another advantage of our tail risk measures over risk-neutral moment estimates extracted from options (e.g., Bakshi and Madan (2000), Carr and Madan (2001), and Bakshi, Kapadia, and Madan (2003), among others) is that the two tail risks are separable. In other words, our LEFT and RIGHT strategies are directly tradable strategies that are designed to load on one risk factor while being orthogonal to the other. The returns on the two strategies are only moderately correlated (-0.48).[3] This feature is essential for investigating the pricing implications of the left- and right-tail risks for the cross-section of stock returns jointly.

Campbell (1996) and Ang, Hodrick, Xing, and Zhang (2006b) point out that candidate pricing factors should be able to forecast the future investment opportunity set. Therefore, we start by investigating the effect of market tail risks on aggregate market returns. Following the literature on equity return prediction, we apply forecasting regressions with monthly data for our 1996-2017 sample. We find that both market left- and right-tail risk factors have strong predictive power for future market returns, and that they are economically important: a two-standard-deviation increase in left-tail (right-tail) risk predicts a decrease (increase) in future excess market annual returns of 22.912% (19.498%), with a adjusted R^2 of 4.620% (3.244%). Furthermore, consistent with the literature, we find that the effect of right-tail risk is less significant when left-tail risk is controlled for, suggesting that the left-tail risk partially dominates the right-tail risk with respect to its impact on aggregate market returns.

Following Ang, Chen, and Xing (2006a) and Cremers, Halling, and Weinbaum (2015), we conduct two types of empirical exercises: portfolio sorts and firm-level cross-sectional regressions.

[3]Kelly and Jiang (2014) estimate realized tail risk from the cross-section of stock returns and find the right-tail risk have a correlation of 81% with left-tail risk.

First, we sort all stocks on the NYSE, Amex, and Nasdaq from 1996 through 2017 in quintiles based on the realized factor loadings at the individual stock level estimated with daily returns. Next, we investigate the contemporaneous relationship between realized factor loadings and stock returns.[4] The results of portfolio sorts show that market right-tail risk is positively priced in the cross-section of stocks, while left-tail risk is negatively priced in a weaker way. We find that stocks with high exposure to innovations in market left-tail (right-tail) risk exhibit low (high) expected returns on average. Specifically, we show that the single-sorted hedge portfolio that buys stocks with high right-tail risk loadings and sells stocks with low right-tail risk loadings yields an annual return of 7.747% (t-statistic 3.656) and an alpha of 7.314% (t-statistic 3.001) with respect to the Fama and French (1993) three-factor model for value-weighted portfolios. When we sort stocks into quintiles based on the sensitivities of their returns to innovations in market left-tail risk, the long/short portfolio that buys stocks with high left-tail risk betas and sells stocks with low left-tail risk betas has an annual return of -6.648% (t-statistic -2.462) and an alpha of -9.688% (t-statistic -3.670). The empirical findings of our univariate portfolio sorts support the hypothesis that market left- and right-tail risks are priced differently in the cross-sectional stock returns and command negative and positive risk premiums, respectively.

Given the negative correlation (-0.48) between market left- and right-tail risks, however, it might be difficult to separate fully the effects of the two tail risks. Therefore, we create portfolios that exhibit differences in LEFT (RIGHT) factor with approximately the same levels of RIGHT (LEFT) factor. To conduct an extensive investigation, we apply both unconditional and conditional double-sorting approaches.

For unconditional double-sorting portfolios, we independently sort all stocks into quintiles on both LEFT and RIGHT factor loadings, resulting in a total of 25 portfolios. As expected, we find significantly positive high-RIGHT minus low-RIGHT portfolio returns for almost all quintiles of LEFT factor loadings. Interestingly, we detect significantly negative return spreads of high-LEFT minus low-LEFT portfolios for only two of five quintiles of RIGHT factor loadings. For conditional double-sorting portfolios, we first perform a sequential sort by creating quintile portfolios ranked by control variables. Then, within each control variable quintile, we form a second set of quintile

[4] Cremers et al. (2015) emphasizes that the contemporaneous relation between factor loadings and risk premiums is fundamental to the cross-sectional risk-return relations.

portfolios ranked on a target variable. We find that the average raw return difference between the high-RIGHT beta and low-RIGHT beta quintiles for a value-weighted portfolio is 4.031% per year (t-statistics 3.581). The average Carhart (1997) four-factor alpha is 3.925% per year (t-statistics 3.571). In addition, the high-minus-low portfolios that are formed based on LEFT betas, while controlling for RIGHT factor loadings, have an average return of -4.233% per year (t-statistics -1.690) and four-factor alpha of -4.294% per year (t-statistics -1.758). Therefore, the risk premium of the LEFT factor becomes less significant after removing the effect of the RIGHT factor. The above results on the cross-sectional pricing implications of market left- and right-tail risks are in contrast to the empirical findings in the related time-series literature that emphasizes the dominating effect of downward jump risk on aggregate market returns.

The second type of empirical exercise we perform is a series of firm-level cross-sectional regressions (e.g., Fama and MacBeth (1973)). Consistent with the findings obtained using portfolio sorts, we continue to find that the risk premium for market right-tail risk is positive and is both economically substantial and statistically highly significant: a two-standard-deviation increase across stocks in market right-tail risk factor loadings is associated with a 4.31% increase in expected annual returns. The estimated premium for bearing market right-tail risk is robust and cannot be explained by known risk factors or firm characteristics. We find, however, that the average slope coefficients on left-tail risk factor loadings less significant when right-tail betas are controlled for, implying that the explanatory power of the left-tail factor loadings is partially subsumed by the right-tail betas.

We extend our work by investigating the predictive power of market tail risk for cross-section stock returns. Although the tail risk has low predictability, they can be hedged in the cross-section of stock returns by estimating the future risk factor loadings on past firm characteristics. We also replicate our main analyses using the cross-section of equity portfolios as test assets. Specifically, we utilize a large number of portfolios that include stocks sorted by the industry, size, book-to-market, investment, and profitability characteristics. Similar to our findings from individual stocks, the results show that market right-tail risk is positively priced in the cross-section of equity portfolios. In addition, we also find that the right-tail risk is significantly positively priced in the cross-section of mutual funds. Furthermore, we show that the market bi-tail risk factor, which is designed to change the value if there is a change in either the left or right tail of the risk-neutral density, does not affect the cross-sectional stock returns, supporting that right-tail risk is not the mirror image of left-tail risk. Therefore, it is essential to analyze market left- and right-tail risks separately.[5]

Finally, we show that our results are robust to 1) using different LEFT and RIGHT factors constructed with alternative selections of option contrasts, 2) performing analysis based on different beta-estimation and return-holding periods, and 3) using alternative measures of negative jump risk that are also constructed from options data (e.g., Yan (2011) and Gao, Gao, and Song (2018)).

This paper is closely related to Kelly and Jiang (2014), who find that the time-varying left-tail risk has strong predictive power for aggregate market returns and can also predict future returns in the cross-section. Our work differs from their study in the following dimensions. First and foremost, we investigate the cross-sectional pricing implications of both left- and right-tail risks. Second, they measure tail risk as a rare extreme downside event, while we study relatively high frequent variations in the two tails of the risk-neutral density of market returns. Last but not least, we measure market tail risks with portfolio trading strategies that are directly tradable, without imposing any restriction on tail behavior.

Our work is also related to recent studies that examine the effect of jump risk on the cross-section of expected stock returns. Yan (2011) finds that stocks with systematic jumps that are more negatively correlated with jumps in the stochastic discount factor earn higher returns. Jiang and Yao (2013) point out that the size and liquidity premiums are all realized in the cross-sectional differences of jump returns. Bollerslev, Li, and Todorov (2016) find that discontinuous betas constructed from high-frequency data are crucial to explaining cross-sectional variation in expected stock returns. These studies, however, do not separate downward jump risk from upward jump risk, and most measure jump risk based on realized jump returns.

The asymmetrical treatment by investors of downside risk versus upside risk has long been recognized among practitioners and academic researchers. Theoretical models have been developed in which investors place different weights on different market extreme conditions in their utility functions (e.g., Bawa and Lindenberg (1977), Gul (1991), Routledge and Zin (2010), and Farago and Tdongap (2018), among others). One important model is the cumulative prospect theory of Tversky and Kahneman (1992). The investor characterized by prospect theory will exhibit asymmetric

[5]The bi-tail risk factor is similar to risk-neutral skewness directly estimated from options data (see., e.g., Bakshi et al. (2003)). The results are similar when we test the pricing implication of risk-neutral skewness in the cross-section stock returns.

sensitivities to the left and right-tails of the return distribution. Researchers in economics and finance also have devoted much effort to testing the relation between tail risk and asset price empirically. Ang et al. (2006a) find that stocks that covary strongly with the market during market declines exhibit high average returns. Lettau, Maggiori, and Weber (2014) show that downside risk is crucial in capturing the cross-sectional variation in returns across asset classes. Gao et al. (2018) document that hedge funds with greater exposure to disaster risk concerns earn higher returns. Xiao (2014) argues that the right-tail distribution information of returns can provide valuable information to investors, and further proposes quantile regression estimators for the right-tail measures. In this paper, by contrast, we develop a new measure for right-tail risk and emphasize the importance of the right-tail risk in explaining cross-sectional stock returns.

Our cross-sectional pricing implications of jump tail risk also complement the empirical findings reported in the option pricing literature. Time-varying jump risk has been shown to be a fundamental factor in determining option prices (see, e.g., Bates (2000), Pan (2002), and Santa-Clara and Yan (2010)). Bates (1991) shows that out-of-the-money puts became unusually expensive during the year preceding the crash of October 1987. Furthermore, the implied volatility of aggregate market index options has been found to be negatively skewed since the 1987 crisis (e.g., Bakshi, Cao, and Chen (1997), Duffie, Pan, and Singleton (2000), and Eraker, Johannes, and Polson (2003), among others). These results indicate that downward jump risk and upward jump risk play asymmetrical roles and that investors may require different risk premiums for bearing different jump risks. As such, Kou (2002) proposes modeling the price jumps as exponentially distributed, with separate tail decay parameters for negative and positive jumps. Using the double exponential specifications of Kou (2002), Bakshi and Wu (2010) find the distinct pricing of downside and upside jumps during the Nasdaq bubble period. Andersen, Fusari, and Todorov (2015) further allow different state variables to govern the time-varying jump intensities of downside and upside jumps, resulting in a significant improvement for the model performance. Although these studies suggest that downward jump risk plays a dominating role in time-series aggregate market returns and, thus, in market option prices, we provide evidence that upward jump risk, which is related to right-tail risk in this paper, is essential in the cross-sectional stock returns.

Finally, our paper connects to the literature focusing on the cross-sectional pricing implications of aggregate risk factors. Ang et al. (2006b) use the first difference in the CBOE VIX index as a proxy for innovations in volatility and find that stocks with high sensitivity to innovations in aggregate stock market volatility have low average returns. Adrian and Rosenberg (2008) document significantly negative prices of both short-run and long-run components of market volatility. Chang, Christoffersen, and Jacobs (2013) consider market skewness estimated from option data and find a negative market price of market skewness. Cremers et al. (2015) show that stocks with high exposure to the aggregate jump risk implied by options prices have low expected returns. Hollstein and Prokopczuk (2017) detect that market volatility-of-volatility, as measured by CBOE VVIX index, commands a significantly negative risk premium. Bali, Brown, and Tang (2017) document that uncertainty-averse investors demand extra compensation for holding stocks with negative uncertainty betas. Unlike the aforementioned studies, we attempt to uncover the underexamined relevance of market right-tail risk to the cross-sectional stock returns.

The paper proceeds as follows. In Section 2, we first discuss the data, as well as the portfolio trading strategies used to measure market left- and right-tail risk. Next, we analyze the properties of our tail risk measures. Finally, we show the empirical framework designed to investigate whether market tail risk are priced. Section 3 presents the empirical results obtained by sorting the cross-section of stocks into quintiles based on their sensitivities to market tail risk and risk premium estimates from cross-sectional regressions. Section 4 extends our main analysis and examines the robustness of our results. Section 5 concludes.

2. Data and Variable Construction

2.1. Data

We obtain the daily stock prices and returns data from the Center for Research in Security Prices (CRSP). We select all stocks traded on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotations (NASDAQ) that are classified as ordinary common shares (CRSP codes 10 and 11) and exclude closed-end funds and real estate investment trusts (Standard Industrial Classification codes 6720-6730 and 6798) for the sample period July 1965 to December 2017. Following Amihud (2002) and Zhang (2006), we exclude penny stocks with prices below \$1. Additionally, we require a market capitalization of at least \$225 million. These two thresholds serve to eliminate the most illiquid stocks that exhibit potential microstructure problems and that may bias the results. We adjust for delisting returns following Shumway (1997) and Shumway and Warther (1999).

We collect data on the S&P 500 index options and Black and Scholes (1973) option sensitivities from IvyDB OptionMetrics. We use the average of bid and ask quotes for each option contract and filter out options with zero bids, as well as those with average quotes less than \$3/8. Next, we filter out quotes that do not satisfy standard no-arbitrage conditions. Finally, we eliminate in-the-money options, which are less liquid than out-of-the-money and at-the-money options.

Accounting data are obtained from Compustat, and we use Kenneth French's online data library to obtain the risk-free rate, market, size, value, and momentum factors.

2.2. Construction of Market Tail Risk Factors

2.2.1. Background

There is a substantial option pricing literature that documents the market tail risk or jump risk is priced in the aggregate market. Pan (2002) shows that jump-risk premia are crucial to reconciling the dynamics of market stock price under the physical and risk-neutral worlds. Eraker et al. (2003) further illustrate that jump risk should command relatively larger risk premia than a diffusive one, as it cannot typically be hedged away and its contribution to periods of market stress is more significant. Both assume, however, that jump size is normally distributed and that jump intensity is controlled by diffusive volatility. Kou (2002) proposes to model the price jumps as exponentially distributed, with separate tail decay parameters for negative and positive jumps. Using the double exponential specification of Kou (2002), Bakshi and Wu (2010) find the distinct pricing of downside and upside jumps during the Nasdaq bubble period. Andersen et al. (2015) further allow different state variables govern the time-varying jump intensities of downside and upside jumps, resulting in a significant improvement for the model performance. Instead of using parametric pricing models, Bollerslev and Todorov (2011) apply a model-free estimation procedure and find that a large portion of the aggregate equity premium could be attributable to jump tail risk.

Although the existence of priced aggregate tail risk has been extensively studied in the literature of time-series pricing, there is less evidence reported in the cross-sectional pricing work. Yan (2011) find that expected stock returns are negatively related to average jump sizes. Chang et al. (2013) show that market skewness earns a negative risk premium. Jiang and Yao (2013) argue that cross-sectional differences in jumps fully account for the size and illiquidity premium. Cremers et al. (2015) show that stocks with high exposure to aggregate jump risk implied from options prices have low expected returns. Bollerslev et al. (2016) find that discontinuous betas constructed from high-frequency data are crucial to explain cross-sectional variation in expected stock returns. These papers, however, do not separate downward jump risk from upward jump risk, and most of them measure jump risk based on realized jumps return.

2.2.2. Variable Construction

We hypothesize that if individual stocks are exposed to market tail risk and investors regard left- and right-tail risk as different risk factors, these two types of factors should explain the cross-section of stock returns and command different premiums. To enable the estimation of exposures of stocks to the left- and right-tail risks, we construct left- and right-tail risk factor-mimicking portfolios. The portfolios are designed to increase the value if the tail risks increase, and thus they represent long tail-risk positions. To isolate the effects of tail risk, we must remove exposure to changes in other moments of the risk-neutral distribution. Therefore, we construct tail-risk factor-mimicking portfolios so that they have no exposure to changes in the underlying movement (Delta neutral) or volatility (Vega neutral).[6]

Specifically, as payoff functions of out-of-the-money puts and calls are determined only by the left and right tails, respectively, we first construct two types of portfolios that are sensitive to only the left tail (LEFT) or only to the right tail (RIGHT). By construction, the LEFT (RIGHT) portfolio is positively correlated with the left (right) tail, and hence its payoff increases as the probability of a dramatic downward (upward) movement of the underlying is increased.

The LEFT portfolio consists of buying one out-of-the-money put, shorting $\mathcal{V}_P^{OTM}/\mathcal{V}_P^{ATM}$ at-the-money puts, and a stock position of $(-\Delta_P^{OTM} + \mathcal{V}_P^{OTM}\Delta_P^{ATM}/\mathcal{V}_P^{ATM})$, where $\mathcal{V}_P^{OTM}$ and $\mathcal{V}_P^{ATM}$ are Vegas of out-of-the-money and at-the-money puts, respectively. The Delta of this portfolio is

[6] Bali and Scott (2013) design similar strategies to create skewness assets and find a strong negative relationship between risk-neutral skewness and the skewness asset returns. We regard them, however, as assets sensitive to the tail risk, as they are sensitive to risks associated with not only skewness but also kurtosis and even higher moments (Song (2012)).

equal to

$$\Delta_P^{OTM} - \mathcal{V}_P^{OTM}\Delta_P^{ATM}/\mathcal{V}_P^{ATM} - \Delta_P^{OTM} + \mathcal{V}_P^{OTM}\Delta_P^{ATM}/\mathcal{V}_P^{ATM} \;=\; 0. \tag{1}$$

And its Vega is

$$\mathcal{V}_P^{OTM} - (\mathcal{V}_P^{OTM}/\mathcal{V}_P^{ATM})\mathcal{V}_P^{ATM} \;=\; 0. \tag{2}$$

Hence, the LEFT portfolio is indeed both Delta- and Vega-neutral. To verify that its payoff is positively correlated with the left tail, we first note that both puts in this portfolio have changes in payoffs only when the left tail of the underlying changes. An increase in the risk-neutral probability of a large down-move in the underlying would correspond to higher payoffs for two puts simultaneously. Because the out-of-the-money put has a more significant increase in payoffs than at-the-money put, the long position in the LEFT portfolio ensures a higher value. Moreover, any changes to the risk-neutral density for prices higher than the strike of at-the-money put do not affect the value of the LEFT portfolio. Therefore, the LEFT portfolio is a left-tail risk factor-mimicking portfolio, and its value will change only due to changes in the left side of the risk-neutral distribution.

The RIGHT portfolio consists of buying one out-of-the-money call, shorting $\mathcal{V}_C^{OTM}/\mathcal{V}_C^{ATM}$ at-the-money calls, and a stock position of $(-\Delta_C^{OTM} + \mathcal{V}_C^{OTM}\Delta_C^{ATM}/\mathcal{V}_C^{ATM})$. As with the LEFT portfolio, the RIGHT portfolio is Delta- and Vega-neutral and is by construction long right tails. Following the arguments made for LEFT portfolio, because the payoffs of both calls are related only to right tail of risk-neutral density of the underlying, an increase in the probability of a large up-move in underlying would generate higher payoffs for two calls; thus, the RIGHT portfolio, as the out-of-money call increases in value more than the at-the-money call. Therefore, the RIGHT portfolio is a right tail-risk factor-mimicking portfolio, and its value is determined only by the right side of the risk-neutral distribution.

The LEFT and RIGHT strategies are directly tradable, and they are constructed to load on one factor while being orthogonal to the other. Using S&P 500 index options, we construct the tail-risk factor-mimicking portfolios and calculate the LEFT and RIGHT portfolios' daily returns as follows. At the close of trading on a given date, we select call and put options whose maturity is closest to 30 days among all options. To construct the factor-mimicking portfolios, we define the at-the-money put (call) contract to be the contract with a Delta closest to -0.5 (0.5) and the out-of-money put (call) contract to be the contract with a Delta closest to -0.1 (0.1). Hence, we pick 4 required options among the closest-maturity options. If data for any of the required options are not available, that observation is omitted from the analyses. We hold each position for one trading day and then pick new option collections the next day. The portfolio daily return is calculated as the total profits resulting from holding the portfolio divided by the entering costs. Daily returns on LEFT and RIGHT portfolios from January 1996 to May 2017 form the basis of our main tests to examine whether individual stocks are exposed to market tail risks, whether the difference in market tail-risk exposures can explain the cross-section of stock returns, and whether left- and right-tail risks are separately priced in the cross-section of stock returns.

2.2.3. Risk Factor Analysis

Panel A in Table 1 presents the summary statistics of LEFT and RIGHT. The LEFT strategy, on average, earns significantly negative returns (-0.0236% daily or -5.95% annually, significant at the 1% level), and the RIGHT strategy on average earns significantly positive returns (0.0094% daily or 2.37% annually, significant at the 5% level). Therefore, both the magnitude and significance level of the LEFT portfolio's average returns are higher than those of the RIGHT portfolio. This result is consistent with the findings of the option-pricing literature that downside jumps are negatively priced while upside jumps are positively priced, and downward jumps are more critical in determining market option prices. Panel A also highlights that the factor returns are volatile and leptokurtic. The distribution of return on the LEFT strategy has positive skewness, while the return on the RIGHT strategy is left-skewed. Therefore, market investors perceive a much higher probability of a large down-move in the market stock price.

[Insert Table 1 near here]

Panel B in Table 1 reports the Pearson correlation among the different factors. $\text{SKEW}^{\text{NonPar}}$ is the non-parametric risk neutral skewness, defined as the difference between the out-of-the-money call and out-of-the-money put implied volatilities. SKEW^{L} is left risk neutral skewness, defined as the difference between the out-of-the-money put and the at-the-money put implied volatilities. SKEW^R is the right risk neutral skewness. SKEW^{BKM} is the risk neutral skewness based on Bakshi et al. (2003). JUMP and VOL are jump and volatility risk factors, respectively (Cremers et al. (2015)).

As expected, the returns on the LEFT and RIGHT strategies are positively correlated with SKEW^L and SKEW^R, respectively. Surprisingly, LEFT and RIGHT have low correlation with SKEW^{BKM}, and even have unexpected signs of correlation with $\text{SKEW}^{\text{NonPar}}$, implying that left- and right-tail risks represent distinct risks from the total skewness risk studied in Chang et al. (2013) and may command different risk premiums. Furthermore, LEFT and RIGHT factors show an extremely low correlation with the JUMP factor and, to a lesser extent, are positive with the VOL factor. Consequently, the market tail risk factors appear distinct from the other factors documented in the previous literature.

[**Insert Figure 1 near here**]

Figure 1 shows the time-series of daily returns of the LEFT and RIGHT strategies. The LEFT strategy is constructed such that it has a positive return if the left tail of the risk-neutral distribution of market return increases. Hence, the top panel indicates that the major crises since 1996 have always induced market fear of a large down-move in the stock. Furthermore, the daily returns on the LEFT strategy are more volatile during the first half of the full sample period, indicating that the overall expectations of market participants are more stable during the second half period. The bottom panel shows that returns on the RIGHT factor experienced a dramatic decrease during the 2008 financial crisis, thus exhibiting highly negative skewness.

[**Insert Figure 2 near here**]

Figure 2 plots the time-series of monthly returns of the LEFT and RIGHT factors. The figure clearly shows that the LEFT (RIGHT) strategy earns a negative (positive) average return and spikes upward (downward) during the 2008 financial crisis.

2.2.4. Time-series Pricing Implications

To examine the effect of market left- and right-tail risk on aggregate market returns, we apply a series of predictive regressions with our tail risk factors as well as other forecasting variables, including book-to-market ratio (BM), earnings price ratio (E/P), dividend price ratio (D/P), stock variance (SVar), and variance risk premium (VRP). Campbell (1996), Ang et al. (2006b), and Chang et al. (2013) argue that successful candidate pricing factors should be able to forecast the future investment opportunity set.

Following the literature on equity premium forecasting (e.g., Bollerslev, Tauchen, and Zhou (2009), Welch and Goyal (2008), Kelly and Jiang (2014), among others), we use monthly data and aggregate our daily returns on the LEFT and RIGHT strategies to monthly returns. The dependent variable is the monthly return on the S&P 500 index. To illustrate economic magnitudes, all reported predictive coefficients are scaled to be interpreted as the effect of a two-standard-deviation increase in the forecasting variables on future annualized returns.

[**Insert Table 2 near here**]

Table 2 reports the results on forecasting market return for our 1996-to-2017 sample. The first two columns show that both market left- and right-tail risk factors have strong predictive power for future market returns. Both tail risks are important economically: a two-standard-deviation increase in left-tail (right-tail) risk predicts a dramatic decrease (increase) in future excess returns of 22.912% (19.498%), a significant effect compared with other predicting variables. Furthermore, the adjusted R^2 of the first two models are 4.620% (LEFT) and 3.244% (RIGHT), substantially higher than those of other predictors (typically in the 1% - 2% range), and are comparable to the adjusted R^2 of VRP (4.912%). The predictive power of left-tail risk remains significant for all bivariate regressions. Only when the variance risk premium is controlled do we observe a slight drop in the predictive coefficient of left-tail risk factor. For the right-tail risk factor, the predictive ability is also robust to including other alternative regressors except for VRP or left-tail risk factor. Therefore, consistent with empirical findings in the literature, we find that left- and right-tail risk factors have different effects on aggregate market returns and that left-tail risk dominates right-tail risk, motivating us to investigate whether their effects on cross-sectional stock returns remain or change.

2.3. *Empirical Framework*

Our research goal is to examine the relationship between market tail risk exposures and cross-sectional stock returns and test whether the market left- and right-tail risks have different premia. We perform research design following a large body of asset-pricing literature and examine the contemporaneous relationship between realized factor loadings and realized stock returns, as a contemporaneous relationship between factor loadings and risk premiums is fundamental to cross-sectional risk-return relations (e.g., Fama and MacBeth (1973), Fama and French (1993), Jagannathan and Wang (1996), Ang et al. (2006a), and Cremers et al. (2015), among others). Furthermore, Ang et al. (2006a) argue that pre-formation factor loadings might be poor predictors of ex-post risk exposures because risk exposures are highly time-varying. Hence, we estimate factor loadings for individual stocks using daily returns over rolling annual periods from the regression:[7]

$$R_{i,t} = \beta_{0,i} + \beta_{\mathrm{MKT},i} \cdot \mathrm{MKT}_t + \beta_{X,i} \cdot X_t + \varepsilon_{i,t} \tag{3}$$

where $R_{i,t}$ is the excess return over the risk-free rate of stock i on day t, MKT_t is the excess return on the market portfolio (the CRSP value-weighted index) on day t, and X_t is the return on either the left- or right-tail risk factor-mimicking portfolio.

To closely follow the work in Ang et al. (2006a) and Cremers et al. (2015), we only include market excess return as a control variable in Equation (3). Ang et al. (2006a) argue that directly including additional factors in the regression in Equation (3) may add a lot of noise. Although we do not include additional possible cross-sectional risk factors when estimating the risk exposures to the LEFT and RIGHT factors in Equation (3), we do control other factors when performing our cross-sectional asset pricing tests.

To test whether market tail risk are priced in the stock market, we first perform portfolio sorts. At the beginning of each month, we sort the stocks into quintiles based on their risk exposures. $\beta_{X,i}$ is estimated over the following year, as in Equation (3). Hence, quintile 1 contains the stocks with the lowest sensitivities to market tail risk, while quintile 5 contains those stocks with the highest risk factor loadings. Moreover, the hedge portfolio (high-minus-low) consists of buying the

[7]For robustness, we also control for other variables (e.g., Fama and MacBeth (1973) three factors and the change of VIX). The results are quantitatively similar.

quintile of stocks with the highest exposures and shorting the stocks in the quintile with the lowest sensitivities to market tail risk. We then calculate the average returns within each quintile over the same examination period (12 months). Since our research design involves successive 12-month periods employing partly overlapping information, it introduces moving average effects. To adjust for this, the reported t-statistics are computed using 12 Newey and West (1987) lags.[8] To ensure that our results are not driven by other factors or firm characteristics known to affect stock returns, we next calculate abnormal returns (alphas) using the Fama and French (1993) three-factor, Carhart (1997) four-factor and Pástor and Stambaugh (2003) five-factor. Finally, we run Fama-MacBeth regressions of 12-month excess returns on the realized LEFT and RIGHT betas estimated over the same 12 months to get their respective risk premiums.

3. Empirical Results

3.1. Summary Statistics for LEFT and RIGHT Betas

For each stock, we estimate factor loadings at the individual stock level using daily returns over rolling annual horizons, as in regression (3). Table A1 of the Internet Appendix presents summary statistics of LEFT betas. Panel A presents the overall descriptive statistics of LEFT betas over the full sample period. LEFT factor loadings are positive on average, negatively skewed, and strongly leptokurtic. Panel B of Table A1 shows the annual statistics of the LEFT betas. The mean of LEFT betas shows significant variation over time. To visualize the temporal variation of factor loadings, Figure 3 plots the time series of the cross-sectional average of the betas. The solid line demonstrates that the LEFT beats show significant cyclical variations over time, with spikes occurring around crises (e.g., the Dot-Com crisis of 2001 and the financial crisis of 2008). Table A2 of the Internet Appendix presents the descriptive statistics of the RIGHT betas. RIGHT factor loadings are close to zero on average and have a similar cross-sectional distribution with LEFT factor loadings. The dashed line in Figure 3 shows that RIGHT betas have a distinct temporal variation from LEFT betas. Furthermore, Tables A1 and A2 show that the standard deviations of both LEFT beta and RIGHT beta have been increasing since the beginning of our sample (January 1996), implying that

[8] The theoretical number of lags required is 11 but, following Ang et al. (2006a) and Cremers et al. (2015), we include a 12th lag for robustness.

market tail risk exposures have become the critical firm characteristic and merit an exploration of their effect on expected returns.

[Insert Figure 3 near here]

Table 3 shows the pairwise correlations of the factor loadings. Like the factors themselves, market tail risk factor loadings are almost uncorrelated with other factor loadings. RIGHT betas show a slightly negative correlation with the SKEW^{BKM}, JUMP, and VOL betas.

Table 4 reports the results from a series of simple single-sorts to further investigate the relationships between market tail risk factor loadings and firm characteristics, which include Fama-French three-factor betas (β_{MKT}, β_{SMB}, β_{HML}), JUMP factor loadings (β_{JUMP}), VOL factor loadings (β_{VOL}), firm size (SIZE), book-to-market ratio (BM), bid-ask spread (BAS), illiquidity (ILLIQ), realized skewness (RSKEW), realized kurtosis (RKURT), coskewness (CSK), and cokurtosis (CKT). Our construction of these different variables follows standard procedures in the literature, as detailed in Appendix A. Consistent with the results discussed above, the portfolio sorts reveal a negative relationship between the LEFT betas and RIGHT betas, and there is no clear link between market tail risk factor loadings and other portfolio characteristics.

[Insert Tables 3 and 4 near here]

Overall, the results indicate that market tail risk factors are distinct from the other market risk factors studied in the previous literature.

3.2. Univariate Portfolio Sorts

To test whether market tail risk factors can explain the cross-sectional variation of stock returns, as implied by Equation (3), we start with single portfolio sorts based on the LEFT and RIGHT betas. At the beginning of each 12-month period, we sort stocks into quintiles based on their realized betas with respect to the LEFT and RIGHT factors over the following 12 months and compute the average portfolio returns over the same 12 months. Rebalancing monthly, we record the excess returns on each portfolio, starting with the first portfolio formation period spanning the first full year of the sample and ending with the last full year of the sample. While we focus on the results from the value-weighted portfolios presented in Table 5, for robustness Table A4 of the Internet Appendix reports the results of equally weighted portfolios.

[Insert Table 5 near here]

For the LEFT risk factor, Panel A of Table 5 reports average returns, Fama-French three-factor alphas, Carhart (1997) four-factor alphas, and Pástor and Stambaugh (2003) five-factor alphas for value-weighted quintile portfolios and for a hedge portfolio comprising long stocks with highest 20% loadings and short stocks with lowest 20% loadings: that is, going long in quintile 5 and short in quintile 1. We find that the average annual raw return obeys a strictly monotonically decreasing pattern, from 13.913% in quintile 1 to 7.265% in quintile 5. The return spread between the high- and low-β_{LEFT} quintile portfolios is statistically significant, with a mean of -6.648% and a t-statistic of -2.462. The differences in returns between quintiles 5 and 1 are very similar if we risk-adjust using the CAPM at -7.305% per year (t-statistic -2.575), the three-factor model at -9.688% per year (t-statistic -3.670), the four-factor model at -10.800% per year (t-statistic -3.360), and the five-factor model, at -6.155% per year (t-statistic -1.739). Consequently, stocks with high exposure to innovations in aggregate market left-tail risk should earn low returns. In other words, the market price of aggregate left risk is negative. This result is consistent with findings in the literature that stocks with high sensitivity to innovations in market downward jump risk provide hedging opportunities for risk-averse investors who dislike large down-side movement in the market. Therefore, investors are willing to pay a premium to hold such stocks, resulting in negative stock returns. The estimated market price of left-tail risk is -6.648% / 1.538 = -4.322%.[9]

Next, we investigate the source of the risk-adjusted return difference between the high-β_{LEFT} and low-β_{LEFT} portfolios by focusing on the economic and statistical significance of the risk-adjusted returns of quintiles 1 and 5. As shown in Panel A of Table 5, almost all alphas of stocks in quintile 1 (low-β_{LEFT} stocks) are significantly positive, while the alphas of stocks in quintile 5 (high-β_{LEFT}) are significantly negative. Hence, the significantly negative alpha spread between high-β_{LEFT} and low-β_{LEFT} is driven by both the outperformance by low-β_{LEFT} stocks and the underperformance by high-β_{LEFT} stocks. These results indicate that investors who seek to insure themselves against extreme events that dramatically worsen future investment opportunities will find stocks with high

[9] Panel A in Table 4 reports that the average β_{LEFT} difference between quintile 5 and quintile 1 is 1.538.

sensitivities to innovations in market left-tail risk attractive and thus require lower expected returns. On the other hand, risk-averse market participants would require extra compensation to hold stocks whose returns are negatively associated with increases in market left-tail risk.

The portfolio formation procedure and the empirical strategy for market right-tail risk are identical to that for market left-tail risk except that stocks are sorted by β_{RIGHT}. Portfolio 1 (Low β_{RIGHT}) contains stocks with the lowest RIGHT factor loadings and Portfolio 5 (High β_{RIGHT}) includes stocks with the highest RIGHT factor loadings. The results for this procedure are reported in Panel B of Table 5. They show that portfolios sorted on β_{RIGHT} typically exhibit a monotonically increasing pattern in their average alphas and returns. The average raw return difference between the High β_{RIGHT} and Low β_{RIGHT} quintiles is 7.747% per year, with a significant New-West t-statistic of 3.747. The strong relationship between market right-tail risk exposure and average return, however, could be driven by other known cross-sectional determinants of expected returns. To resolve such concerns, we control for systematic risk and find a similar abnormal return for the high-minus-low portfolio of 7.461% per year (t-statistic 3.656). Controlling for the Fama and French (1993) factor (three-factor), the Carhart (1997) factors (four-factor), as well as the Pástor and Stambaugh (2003) factor (five-factor) leads to alphas of 7.314%, 5.666%, and 8.401% per year, respectively, all significant at 1%. The results indicate that stocks whose returns are more positively related to market right-tail risk earn higher returns, implying a positive risk premium of market right-tail risk. This makes sense economically, as this type of stock has low payoffs when investors are poorer (and thus marginal utility is high) and large payoffs when investors are richer (and marginal utility is low). This negative correlation between marginal utility and payoffs of stocks that have positive sensitivity to innovations in market right-tail risk makes such stocks less desirable, such that in equilibrium investors should demand a premium for holding them. The estimated market price of right-tail risk in Table 5 is 7.747% / 1.433 = 5.406%.[10]

As reported in Panel B of Table 5, all alphas of stocks in quintile 5 (high-β_{RIGHT} stocks) are significantly positive, while the alphas of stocks in quintile 1 (low-β_{RIGHT}) show less significant differences from 0. Therefore, in contrast to the result of portfolio sorts based on β_{LEFT}, the significantly positive alpha spread between high-β_{RIGHT} and low-β_{RIGHT} is mostly due to the out-performance of the high-β_{RIGHT} stocks. This result indicates that investors would demand extra

[10] Panel A in Table 4 reports that the average β_{RIGHT} difference between quintile 5 and quintile 1 is 1.433.

compensation in the form of a higher expected return to hold these stocks with high-β_{RIGHT}. Because such stocks have large payoffs only when the market is expected to perform extremely well, they are less desirable.

[Insert Figure 4 near here]

To investigate the time-series of excess returns of the high-minus-low hedge portfolios, we plot the cumulative returns of the LEFT and RIGHT risk hedge (value-weighted) portfolios in Figure 4. To obtain a time-series of monthly returns, we average the returns of all active portfolios during that month. The solid line represents LEFT hedge portfolio returns, while the dashed line corresponds to RIGHT hedge portfolio returns. Over the entire sample period, the cumulative excess returns of LEFT and RIGHT hedge portfolios are rough -80% and 110%, respectively. The trend of the solid (dashed) line, in general, is negative (positive), but there are also periods for which the insurance strategy pays off and the LEFT (RIGHT) hedge portfolio yields significantly positive (negative) returns. Notably, during the Asian crisis of 1997, the Dot-Com bubble in 2000, the 9-11 terrorist attacks of 2001, and the financial crisis of 2008, investors worried about the strike of downward jumps within a short time window as well as strengthened market turbulence, and such a view is reflected in the fatter left tail of the risk-neutral distribution of market stock returns. Therefore, the LEFT hedge portfolio that has positive exposure to left-tail risk yields positive returns. In addition, during these times, market participants believe the probability of large up-move in underlying is low, resulting in a thinner right tail of the risk-neutral distribution and negative returns for the RIGHT hedge portfolio.

In sum, univariate portfolio sorts indicate that both left- and right-tail risks are priced in the cross-section. Specifically, the left-tail risk has a negative risk premium, but the right-tail risk is positively priced. Inconsistently with the literature of time-series estimates of the equity risk premium, however, the results show that the forward-looking left-tail risk is priced in a somewhat weaker way than the right-tail risk in the cross-section, in terms of the magnitude of the market price of risk and significance levels of return spread and alphas.

3.3. Bivariate Portfolio Sorts

Our univariate portfolio reveals that stocks with high left-tail (right-tail) risk betas tend to have low (high) returns. As indicated in Table 3 and Figure 3, however, there is a negative relationship between LEFT and RIGHT factor loadings. To further investigate the relationship between LEFT and RIGHT factor loadings of any given stock, we calculate the portfolio transition matrix. Table A3 of the Internet Appendix reports the time-series mean of the portfolio transition matrix. Specifically, the entry (i, j) in Table A3 represents that a stock in quintile i ranked by β_{LEFT} (as defined by the rows) will be in quintile j ranked by β_{RIGHT} (defined by the columns) at the same time. If the LEFT and RIGHT factor loadings are completely independent, then all the probabilities should be approximately 20%. Instead, Table A3 shows that stocks belonging to low (high) β_{LEFT} portfolios are also more likely assigned to high (low) β_{RIGHT} portfolios. More specifically, Table A3 shows that stocks in the quintile 1 (quintile 5) portfolio ranked by β_{LEFT} have a 49.2% (50.4%) chance of appearing in the quintile 5 (quintile 1) portfolio sorted by β_{RIGHT}. Therefore, to dissect the effects of market tail risk, we need to create portfolios that exhibit differences in one factor with approximately the same levels of the other factor.

First, we apply the unconditional double-sorting approach. Specifically, at the beginning of each month, we independently sort all stocks into quintiles on both LEFT and RIGHT factor loadings, resulting in a total of 25 portfolios. Thus, we obtain quintile portfolios on the exposure to one of the market tail risk while controlling for another one. For each quintile of both sorting variables we obtain a high-minus-low hedge portfolio by buying portfolio 5 and selling portfolio 1 in the quintile. Within each of the 25 portfolios, we weight the stocks by their relative market value at the beginning of the portfolio formation.

[Insert Tables 6 near here]

Panel A in Table 6 reports the results of unconditional double-sorting portfolio sorts. Given that the market prices of risk on LEFT and RIGHT factors appear to be negative and positive, respectively, stocks with low LEFT factor loadings and high RIGHT factor loadings should have high average returns, while stocks with reverse properties (high β_{LEFT} and low β_{RIGHT}) should have low average returns. Furthermore, within each quintile of LEFT factor loadings, stocks with higher RIGHT factor loadings should earn higher returns. Conversely, for each quintile of RIGHT factor loadings, stocks that have high exposure to the LEFT factor should earn lower returns. This is precisely the pattern we find in panel A of Table 6. Portfolios with the lowest β_{LEFT} and highest β_{RIGHT} (portfolio (1,5)) have the highest average return of 15.456% per year, and portfolios with highest β_{LEFT} and lowest β_{RIGHT} (portfolio (5,1)) have the lowest average return of 5.754% per year. For all quintiles of LEFT factor loadings, we find significantly positive high-minus-low RIGHT portfolio returns except for quintile 2. Interestingly, for RIGHT factor quintiles, we detect significantly negative spread returns of high-minus-low LEFT portfolios only for the first two quintiles, although each quintile has the expected high-minus-low portfolio returns and returns pattern: with increasing β_{LEFT}, the returns decrease. Therefore, the right risk factor has a stronger ability to explain the cross-sectional variation of stock returns than does the left risk factor, although they are priced differently in the cross-section. This is consistent with the results of univariate portfolio sorts, which indicate that left-tail risk is priced in a somewhat weaker way than the right-tail risk in the cross-section, in terms of the magnitude of market prices of risk and the significance levels of return spread and alphas.

To complement the above results, we further apply the conditional double-sorting approach. We first perform a sequential sort by creating quintile portfolios ranked by the control variable (either LEFT or RIGHT factors). Then, within each control variable quintile, we form a second set of quintile portfolios ranked on the target variable. This creates a set of portfolios with similar control variables and spreads in the target variable, and thus we can examine the expected return differences due to target variable rankings controlling for the effect of the control variable. We hold these portfolios for 12 months but rebalance them monthly.

Panel B of Table 6 reports the results of bivariate portfolios sorts when we control for RIGHT risk factor and try to examine the effect of LEFT factor. This produces portfolios with different LEFT factor loadings after controlling for the information contained in RIGHT betas and allows us to examine the explanatory power of LEFT betas while controlling for RIGHT betas. Consistent with the above results, we find that the largest average portfolio return of 18.326% per year is found at the bottom left-hand corner (portfolio (5,1)) of Panel B. Conversely, the smallest average portfolio return of 5.323% per year lies in the top right-hand corner (portfolio (1,5)). Furthermore, we observe a negative relationship between increasing β_{LEFT} and lower average returns in every β_{RIGHT} quintile. Within each β_{RIGHT} quintile, the average return differences between the High

β_{LEFT} and Low β_{LEFT} portfolios are in the range of -2.388% to -7.742% per year, but only three of these five return spreads are statistically significant: quintiles 3, 4, and 5. The last two rows of Panel C average the differences between the first and fifth β_{LEFT} quintiles across the β_{RIGHT} quintiles. This summarizes the returns to LEFT factor loadings after controlling for the RIGHT betas. The average return difference is -4.233% per year, with a t-statistic of -1.690, and the FFC4 alpha is -4.294%, with a t-statistic of -1.758. Both average return spread and FFC4 alpha, however, are only significant at the 10% level. Thus, there is a negative relationship between β_{LEFT} and stock returns in the cross-section after taking out the effect of the RIGHT factor loadings.

Panel C of Table 6 repeats the same exercise as Panel B but performs a sequential sort first on LEFT factor loadings and then on RIGHT betas. As we move across the columns in Panel B, the returns generally increase from Low to High RIGHT factor loadings. Similar to unconditional double-sorted portfolios, the largest average portfolio return of 19.108% per year is found at the top right-hand corner (portfolio (1,5)) of Panel B. Conversely, the smallest average portfolio return of 4.408% per year lies in the bottom left-hand corner (portfolio (5,1)), where the highest LEFT factor loadings and the lowest RIGHT factor sensitivities correspond to the lowest stock returns.

In a given LEFT factor loadings quintile, we can take the differences between the last and first RIGHT factor return quintiles, then average these return differentials across the LEFT factor loadings portfolios. This procedure creates a set of RIGHT factor portfolios with nearly identical levels of LEFT factor sensitivities. Thus, we create portfolios ranking on right-tail risk exposures but controlling for left-tail risk factor loadings. If the return differential is entirely explained by the LEFT factor, no significant return differences will be observed across the RIGHT factor quintiles. These results are reported in the last two columns. All of these return differences are highly statistically significant except for that of quintile 2. Panel B of Table 6 shows that the average raw return difference between the High β_{RIGHT} and Low β_{RIGHT} quintiles is 4.031% per year, with a t-statistic of 3.581. The average four-factor alpha (FFC4 Alpha) is 3.925% per year, with a t-statistic of 3.571. Therefore, the result is consistent with the hypothesis that aggregate market right-tail risk is positively priced in the cross-sectional stock returns and that investors require a premium to hold stocks with high exposure to market right-tail risk.

3.4. Cross-Sectional Regressions

The portfolio sorts present strong evidence that market left-tail (right-tail) risk is negatively (positively) priced in cross-sectional stock returns, as the average return of the long-short portfolios constructed based on β_{LEFT} (β_{RIGHT}) is significantly negative (positive). In other words, stocks with high sensitivity to innovations in market left-tail (right-tail) risk have low (high) expected returns. Furthermore, the double sorts indicate that the positive relationship between RIGHT factor loadings and stock returns persists when controlling for, and hence cannot be explained by, LEFT betas. We find, however, that the effect of market left-tail risk exposures is less significant when RIGHT betas are controlled, implying that the variation of RIGHT factor loadings can partially explain the negative relationship between LEFT factor loadings and cross-sectional returns. Following on from that, in this section, we estimate the Fama and MacBeth (1973) regressions of stock returns onto the realized betas with respect to the two market tail risk factors and other known determinants of returns. Specifically, we run the following cross-sectional regression:

$$R_{i,t} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{\text{LEFT},i,t} + \lambda_{2,t} \cdot \beta_{\text{RIGHT},i,t} + \lambda_{3,t} \cdot X_{i,t} + \varepsilon_{i,t} \tag{4}$$

where $R_{i,t}$ is the excess return over the risk-free rate of stock i on day t and $X_{i,t}$ is a collection of stock-specific control variables observable at time t for stock i. $\lambda_{1,t}$ and $\lambda_{2,t}$ denote the market prices of LEFT and RIGHT factor risk, respectively. We continue to work with annual returns regressed on the contemporaneously realized betas, which are obtained for each stock using daily data and estimated using the regression in Equation (3). As before, we are interested in contemporaneous effects. We estimate the regression in Equation (4) across stocks i at time t and then report the cross-sectional coefficients averaged across the sample. Lo and MacKinlay (1990) and Lewellen, Nagel, and Shanken (2010) argue against the use of portfolios in cross-sectional regressions, since the particular method by which the portfolios are formed can strongly influence the results. Furthermore, Ang, Liu, and Schwarz (2020) show that creating portfolios ignores important information about individual factor loadings and leads to higher asymptotic standard errors in risk premium estimates. To compute the standard errors, we take into account potential autocorrelation and heteroscedasticity in the cross-sectional coefficients, and we compute Newey and West (1987)

t-statistics on the time series of slop coefficients.

[Insert Table 7 near here]

Table 7 presents firm-level cross-sectional regressions with RIGHT and LEFT factor loadings first introduced individually and then simultaneously, together with controls for firm characteristics and risk factors. We also include RIGHT and LEFT betas simultaneously in multivariate regressions with control variables to determine their joint effects on stock returns. The first column of Table 7 shows the result of cross-sectional regressions of excess stock returns on the RIGHT factor loading, β_{RIGHT}, controlling only for the market return in model (1). The result is consistent with the findings from portfolio sorts and confirms that market right-tail risk is priced in the cross-section of returns and that the market price of right-tail risk is positive, with an estimated market risk premium of 0.034 (t-statistic 3.410). Consequently, using the time-series mean of the cross-sectional standard deviations of β_{RIGHT} reported in Table A2, namely, 0.634, we estimate that a two-standard-deviation increase in a stock's exposures to market right-tail risk is associated with a 4.31% increase in its average annual returns ($2 \times 0.6344 \times 0.034 = 0.0431$).

Adding additional control variables in the following models, including market beta (BETA), firm size (SIZE), book-to-market ratio (BM), bid-ask spread (BAS), illiquidity (ILLIQ), JUMP factor loadings (JUMP), coskewness (CSK), cokurtosis (CKT), realized skewness (RSKEW), and realized kurtosis (RKURT), does not change our main results about the RIGHT factor. The risk premium estimate for RIGHT risk remains economically large, with values ranging from 0.019 to 0.034 and highly significant for every specification.

Model 2 in the second column of Table 7 shows the result from cross-sectional regressions of excess stock returns on the LEFT factor loading, β_{LEFT}, controlling only for the market return. Consistent with the findings in portfolio sorts, we continue to find that stocks with high sensitivity to innovations in aggregate market left-tail risk earn low returns. To gauge the economic importance of aggregate market left-tail risk, we calculate the drop in the expected rate of return associated with a two-standard-deviation increase across the stocks in β_{LEFT}. Given the time-series average of the cross-sectional standard deviation of β_{LEFT} (0.670) reported in Table A1, the corresponding decrease in expected returns is 3.75%. This effect remains essentially unchanged if we control for other variables in the Fama-MacBeth regressions.

Turning to regression models, including both market tail risk factors, most models show that the β_{LEFT} becomes insignificant when β_{RIGHT} is controlled, indicating that the explanatory power of the LEFT beta is partially subsumed by the RIGHT factor loadings. Importantly, the last column in Table 7, which corresponds to the cross-sectional regression model, including all canonical characteristics, shows that the risk premium of RIGHT factor remains significantly positive but that the risk premium of LEFT factor is insignificantly different from zero, suggesting that the premium for market left-tail risk is fully absorbed by the premiums for the market right-tail risk and the other explanatory variables. In addition, from the last model, we find that the market beta risk premium is significantly positive, consistent with the standard CAPM, that significantly positive premiums for ILLIQ and RKURT are consistent with the empirical findings in Amihud (2002) and Amaya, Christoffersen, Jacobs, and Vasquez (2015), respectively, that significantly negative estimates for CSK and RSKEW are in line with the empirical evidence reported in Harvey and Siddique (2000) and Amaya et al. (2015), and that market jump risk is negatively priced, as shown in Cremers et al. (2015). Consistent with the recent findings reported in An, Ang, Bali, and Cakici (2014) and Hollstein and Prokopczuk (2017), we detect that the risk premiums for SIZE and BM are positive and that the premium for BAS is negative.

In summary, in this section, we continue to find that market left- and right-tail risks are priced negatively and positively, respectively, in the cross-section of stock returns. Compared with portfolio sorts, however, the firm-level cross-sectional regressions show that only the risk premium for RIGHT factor is both economically substantial and statistically highly significant, while the premium for LEFT factor is partially absorbed by the premiums for the RIGHT factor and other explanatory variables. Consequently, the result of the Fama-MacBeth regressions emphasizes the significant effect of market right-tail risk on cross-sectional stock returns, while such an effect has not been uncovered in the literature. Interestingly, unlike the empirical findings in the related time-series (or option-pricing) literature, the results here indicate that market participants have greater consideration for market right-tail risk than market left-tail risk, as they appear to be less willing to hold stocks with high exposure to innovations in aggregate market right-tail risk, and thus, in equilibrium, demand a high premium for holding such stocks.

4. Extensions and Robustness Checks

4.1. Predicting Future Stock Returns and Factor Loadings

So far, we focus on contemporaneous relations between market left- and right-tail risk loadings and firm returns. The previous analysis strongly indicates that market left- and right-tail risk are priced in the cross-section of stock returns, but, for practical purposes, how these risk can be hedged is also of interest. Therefore, in this section, we investigate whether future LEFT and RIGHT loadings can be predicted in order to form an ex-ante hedging strategy.

We first examine the relation of average returns and past factor loadings. Specifically, at the beginning of each month, we form quintile portfolios based on the stocks's past sensitivities to market left- or right-tail risk over the past 12 months $(t-12, t-1)$ and then compute average returns over the next 12 months $(t, t+11)$. Table 8 reports the results. Sorting the stocks by past exposure to LEFT or RIGHT does not produce a significant spread in average returns and in factor alphas. This indicates that the market tail risk loadings are strongly time-varying, such that simply using past loadings does not result in consistent exposures to market tail risk.

[Insert Tables 8 and 9 near here]

We next test the cross-sectional predictability of several ex-ante firm characteristics and factor loadings for future betas with respect to LEFT or RIGHT factor. Specifically, we run Fama-MacBeth regressions in which cross-sectional predictors are measured during the 12 months directly prior to the 12-month estimation period for sensitivities to market left- or right-tail risk. The results are reported in Table 9. Panel A shows the coefficient estimates from the regression in which LEFT betas are the dependent variable. We find that, in univariate specifications, realized LEFT betas alone can positively predict future LEFT loadings, but the average coefficient is economically small. Furthermore, when we include all lagged firm characteristics the coefficient of past LEFT loadings become insignificant. Hence, there appears to be large time-variation in LEFT loadings. The best predictors for future LEFT betas are past BETA and ILLIQ with a positive sign and BAS, CKT and RSKEW with a negative sign. In Panel B, we also find that past RIGHT betas are poor predictor for future RIGHT loadings. Furthermore, it seems that CKT, RSKEW, realized jump risk betas and CSK robustly predict future RIGHT loadings.

4.2. Equity Portfolio Analysis

In Section 3, we find strong evidence that market-right tail risk is priced in the cross-section stock returns. In this section, we proceed by examining the relation between market tail risk and the cross-section of equity portfolios. Following Bali et al. (2017), we download from Kenneth French's data library the daily returns on 49-industry portfolios and 100 portfolios (10×10 bivariate) formed on size and book-to-market, size and investment, and size and profitability (a total of 349 portfolios).

We estimate LEFT and RIGHT loadings using Equation (3) and then follow the method described in Section 2. Panel A in Table 10 presents results from univariate portfolio sorts on LEFT or RIGHT loadings. We continue to find that market right-tail risk is significantly positively priced. The hedge portfolio that buy higest RIGHT betas and sell lowest RIGHT betas has significant positive return (2.881%, $t = 2.771$). Furthermore, the difference in alphas between the high-β_{RIGHT} and low-β_{RIGHT} is 2.491 ($t = 2.423$) for CAMP model; 2.244 ($t = 2.224$) for three-factor model; 2.391 ($t = 2.350$) for four-factor model and 3.017 ($t = 2.494$) for five-factor model. However, the return and alphas differences of long/short portfolio formed on β_{LEFT} are all insignificant.

[Insert Table 10 near here]

We next perform conditional double sorts on LEFT and RIGHT loadings following the same procedure as we use in Section 3. Panel B shows that, consistent with the results from Panel A, market right-tail risk is significantly priced in the cross-section equity portfolios and its risk premium cannot be explained by market left-tail risk. More specifically, the Panel B shows that the average return spread of long/short portfolios based on β_{RIGHT} controlling for β_{LEFT} is 2.634% with a high t-statistics of 2.230. The four-factor alpha is 2.357% with a t-statistics of 2.160. However the return spread of long/short portfolios based on β_{LEFT} is insignificant when β_{RIGHT} is controlled.

4.3. Mutual Funds Analysis

In this section, we investigate whether the positive relation between right-tail risk and contemporaneous returns that we have documented at the stock-level also translates to the fund-level. To do so, we collect a sample of mutual funds from the CRSP Survivor Bias Free U.S. Mutual Fund Database.

[Insert Table 11 near here]

We estimate LEFT and RIGHT loadings using Equation (3) and then follow the method described in Section 2. Panel A in Table 11 compares the annual returns of fund quintiles formed based on β_{RIGHT} and β_{LEFT}. The results indicate that market right-tail risk is significantly positively priced. Specifically, the abnormal return difference between quintiles that include the funds with the highest and lowest β_{RIGHT} is equal to 2.261% with a t-statistic of 2.672. However, the return difference of long/short portfolio formed based on β_{LEFT} is insignificant. We next perform conditional double sorts on β_{RIGHT} and β_{LEFT}. In Panel B, we continue to find that the market right-tail risk is significantly priced in the cross-section mutual funds. As we move across the columns, the returns generally increase from low to high β_{RIGHT}. The average return difference between the high-β_{RIGHT} and low-β_{RIGHT} quintiles is 3.029% with a t-statistics of 3.653. However, the left-tail risk is not priced at the fund-level.

4.4. Market Bi-Tail Risk

The results on our baseline analysis motivate us to consider market left- and right-tail risk as a whole. To incorporate both tail risk, we design a new factor-mimicking portfolio named Bi-Tail. Specifically, the Bi-Tail portfolio consists of buying one out-of-the-money call, shorting $\mathcal{V}_C^{OTM}/\mathcal{V}_P^{OTM}$ out-of-the-money puts, and a stock position of $(-\Delta_C^{OTM} + \mathcal{V}_C^{OTM}\Delta_P^{OTM}/\mathcal{V}_P^{OTM})$, where $\mathcal{V}_C^{OTM}$ and $\mathcal{V}_P^{OTM}$ are Vegas of out-of-the-money calls and puts, respectively, and Δ is the Delta of options. It can be verified that the Bi-Tail portfolio is Delta- and Vega-neutral, and its value is both positively correlated with the right tail and negatively correlated with the left tail. In contrast to the LEFT or RIGHT portfolio, the Bi-Tail portfolio considers relative changes in the right and left tail of the risk-neutral density of the underlying stock. In addition to the portfolio trading strategy method, we also directly measure market bi-tail risk by SKEW^{BKM}, which previous studies have shown to be related to tail risk.

[Insert Table 12 near here]

Table 12 reports the results of univariate portfolio sorts based on Bi-Tail and SKEW^{BKM} betas. The average returns and alphas of long/short portfolios are all positive, but none are significant.

Interestingly, the insignificantly positive risk premium of risk-neutral skewness measured by Bakshi et al. (2003) stands in contrast to the significantly negative risk premium reported in Chang et al. (2013). The positive risk premium of risk-neutral skewness risk, however, is somewhat consistent with our findings and economic intuition, as we find that a left or right tail risk commands a negative or positive risk premium, respectively. Importantly, the insignificant results indicate that market participants consider the left and right tail risks separately instead of perceiving them as a whole. Broadly speaking, investors seem concerned about increases in the probability of a large upward (downward) movement of the market only from the right (left) side of the risk-neutral density of the market index, rather than considering the relative changes in the two sides.

4.5. Equal-Weighted Portfolio Analysis

The results of value-weighted long/short portfolios might be dominated by few big stocks (Fama and French (2008)). Therefore, for robustness, Table A4 of the Internet Appendix presents the result of univariate portfolio sorts by forming equally weighted portfolios.

Panel A.1 of Table A4 reports the average returns and risk-adjusted alphas of portfolios sorts based on the LEFT risk factor. Consistent with the findings in Table 5, we continue to find that the average annual raw return obeys a nearly monotonically decreasing pattern, from 23.177% in quintile 1 to 18.944% in quintile 5. The average of the return spreads between the high- and low-β_{LEFT} quintile portfolios, however, is only significant at the 10% level, with a mean of -4.233% and a t-statistic of -1.702. The difference in returns between quintiles 5 and 1 is very similar if we risk-adjust the returns using different factor models. Consequently, stocks with high exposure to innovations in aggregate market left-tail risk should earn low returns, although the significance of the abnormal returns of the long/short portfolio is typically slightly weaker.

Panel A.2 of Table A4 shows that the portfolios sorted on β_{RIGHT} in general exhibit a monotonically increasing pattern in their average alphas and returns. The average raw return differentials between the High β_{RIGHT} and Low β_{RIGHT} quintiles is 6.183% per year, with a significant Newey-West t-statistic of 4.751. Furthermore, the average alphas of all factor models have a similar magnitude and are significant at 1% (except the 5-factor alpha).

Panel B of Table A4 shows double-sorted portfolios based on the RIGHT and LEFT betas. Panel B.2 shows that the average return spread of long/short portfolios based on β_{RIGHT} controlling for

β_{LEFT} is 4.202%, with a high t-statistics of 3.157%. The return spread of long/short portfolios based on β_{LEFT}, however, is insignificant when β_{RIGHT} is controlled. These results further support that the market right-tail risk is essential to cross-sectional stock returns and commands a significantly positive risk premium.

4.6. Alternative Selections of Option Contrasts

Table A5 of the Internet Appendix reports the results of empirical exercises with which we closely follow our baseline analysis, except that we select contracts with the specific strike-to-price ratios. Specifically, we define out-of-the-money put (call) as the option with a strike-to-price ratio closest to 0.95 (1.05). Panel A of Table A5 presents the quintile returns of single-sorted portfolios based on new factor loadings. The return patterns observed in the previous analyses remain. The high-minus-low returns of the RIGHT hedge portfolio are significantly positive, with a mean of 7.392% per year and a t-statistic of 3.313. The average return spreads of the LEFT hedge portfolio is -5.056%, with a t-statistic of -1.950. Panel B of Table A5 shows double-sorted portfolios based on the RIGHT and LEFT betas. Consistent with the findings in Table 6, market right-tail risk is significantly priced in the cross-sectional stock returns and commands a positive risk premium. The effect of market left-tail risk on cross-sectional stock returns, however, becomes less significant after taking out the impact of right-tail risk.

Table A6 of the Internet Appendix reports risk premium estimates and further demonstrates that the right-tail risk premium partially absorbs the premium for left-tail risk because the negative risk premium of left-tail risk becomes less, even insignificant, when right-tail risk is controlled.

4.7. Alternative Beta Estimation and Return Holding Periods

Our baseline analyses are based on betas estimated from returns over 12 months. We emphasize that the choice of a 12-month examination period is typically used to test the contemporaneous relationship between risk factors and stock returns in the literature (e.g., Ang et al. (2006a), Cremers et al. (2015), Hollstein and Prokopczuk (2017), and among others). To assess the robustness of our results across different examination periods, we perform the portfolio sort exercises with 1-, 3-, and 6-month horizons.

Table A7 of the Internet Appendix shows that, in the case of a 1-month examination period, both LEFT and RIGHT factors have an insignificant effect on cross-sectional stock returns, although the quintile portfolios have the expected sign of the high-minus-low portfolio returns and returns pattern.[11] This lack of statistical significance may be due to the estimation noise induced by insufficient points estimation. As showed in Tables A1 and A2, risk factor loadings exhibit significant cross-sectional and time-series variations. In the case of the 3-month examination period, the result shows that portfolios sorted on β_{RIGHT} typically exhibit a monotonically increasing pattern in average returns. The average return spreads between the High β_{RIGHT} and Low β_{RIGHT} quintiles is 7.163% per year (t-statistic 3.892), very close to the annual return of 7.747% on the long/short 12-month portfolio reported in Table 5. Furthermore, risk-adjusted returns are highly statistically significant in all models. As expected, the 6-month portfolio sorts show a similar result with respect to market right-tail risk (annual return 6.225% and t-statistic 3.504). Interestingly, compared with market right-tail risk, the left-tail risk has a small effect on the cross-section stock returns for both the 3- and 6-month examination periods, given the magnitudes of the return spreads and t-statistics. The above results are consistent with our baseline findings that market right-tail risk is positively priced in the cross-section stock returns, while the left-tail risk is negatively priced in a weaker way.

4.8. Alternative Measures of Tail Risk

The baseline analyses show that market right-tail risk is distinct from left-tail risk and positively priced in the cross-sectional stock returns in a stronger way. Recent studies, however, indicate that investors are more concerned about downside jump risk. Therefore, we next investigate whether our results are robust to the use of alternative non-tradable downside jump risk measures. The construction of upside jump risk rarely appears either in the time-series behavior of the aggregate stock market or in cross-sectional asset pricing studies. The estimated upside jump risk usually exhibits an extremely negative correlation (around -0.8) with the downside jump risk reported in the previous studies. We show, however, that they have only a relatively low correlation of -0.48 by constructing portfolio strategies that load on one factor but are orthogonal to the other. Furthermore, we study the effect of relatively more frequent tail risks with smaller size instead of rare extreme risks. Therefore, our experimental design focuses on a test of whether the effect of

[11] All returns and alphas reported in Table A7 are annualized.

our proxy for market right-tail risk remains significant after controlling for alternative measures of left-tail risk.

Yan (2011) proposes to measure downward jump risk by the change in the slope of the implied volatility skew, as the skew is approximately proportional to the product of jump intensity and average jump size. Therefore, our first alternative measure of downward jump risk (IV-Slope) is the difference between the implied volatility of an out-of-the-money put option (-0.2 Delta) and an at-the-money call option (0.5 Delta).

Based on the results of Gao et al. (2018) design a new measure of rare disaster concern index (RIX). They show that RIX captures all the high-order moments of the jump distribution with negative sizes, given that the price process follows the Merton (1976) jump-diffusion model. Thus, RIX and IV-Slope are those most similar ones to our left-tail risk measures.

[**Insert Table 13 near here**]

The evidence in Table 13 shows that our results for the pricing of market right-tail risk are quite robust to the use of different alternative measures. Consistent with our baseline results in Table 7, in all model specifications, the RIGHT risk factor commands a significantly positive premium after controlling for alternative left-tail risk proxies. In contrast with the insignificantly negative risk premium of the LEFT factor reported in Table 7, both IV-Slope and RIX are significantly priced in the cross-section of stock returns. This difference may be due to the construction of alternative downward jump risk proxies-they are also affected by other risk, such as the underlying movement and volatility risks. The LEFT factor, however, by construction, is both Delta- and Vega-neutral. Consequently, the market right-tail risk is distinct from the left-tail risk and carries a positive and statistically significant market price of risk.

5. Conclusion

We provide a method to separate market right-tail risk from market left-tail risk and measure them by constructing tradable portfolio strategies on market index options so as to load on one risk factor while being orthogonal to the other.

We then investigate the pricing implications of market tail risks for the cross-section of stock returns, using both univariate and bivariate portfolio sorts based on our left- and right-tail risk factor loadings. We find that the quintile of stocks with the highest exposure to innovations in market left-tail (right-tail) risk underperforms (outperforms) the quintile of stocks with the lowest sensitivity toward market left-tail (right-tail) tail risk by 6.65% (7.75%) per year for value-weighted portfolios. We find that market right-tail risk is more strongly priced than left-tail risk.

Next, we dissect the effects of market tail risks by applying firm-level cross-sectional regressions to estimate the risk premiums for aggregate market left- and right-tail risks. Consistent with the findings obtained using portfolio sorts, we continue to find that the risk premium for market right-tail risk is positive and both economically substantial and statistically highly significant: a two-standard-deviation increase across stocks in market right tail risk factor loadings is associated with a 4.31% increase in expected annual returns. The estimated premium for bearing market right-tail risk is robust and cannot be explained by other known risk factors, such as the market excess return, size, book-to-market, or market jump risk factors, or by other firm characteristics. We also find, however, that the average slope coefficients on the left-tail factor loading are less significant, even insignificant, when right-tail betas are controlled, implying that the right-tail risk partially subsumes the explanatory power of the left-tail risk. This result stands in contrast to the empirical findings in the time-series (or, option pricing) literature, which suggest that aggregate downward jump, which is related to the left-tail risk in this paper, plays a dominating role in determining option prices, and that the significant risk premium of down-side jump is required to reconcile with the dynamics of market price in the physical and risk-neutral world.

Finally, we show that the market bi-tail risk factor, which is designed to change value if there is a change in either the left or right tail of the risk-neutral density, has no effect on the cross-sectional stock returns. Therefore, market participants pay more attention the market right-tail risk than to the left- or bi-tail risk, as they appear to be less willing to hold stocks with high exposure to innovations in market right-tail risk, and thus, in equilibrium, demand a high premium for holding such stocks.

Appendix A. Variable Definitions

A.1. *In Forecasting Regressions*

- Dividend Price Ratio (D/P) is the difference between the log of dividends and the log of prices, where dividends are 12-month moving sums of dividends paid on the S&P 500 index. Data are from Amit Goyals website.
- Earnings price ratio (E/P) is the difference between the log of earnings and the log of prices, where earnings are 12-month moving sums of earnings on the S&P 500 index. Data are from Amit Goyals website.
- Stock variance (SVAR) is the variance of stock returns calculated by summing squared daily returns on the S&P 500 index.
- Book-to-market ratio (BM) is the ratio of book value to market value for the Dow Jones Industrial Average. For the months from March to December, this is computed by dividing book value at the end of the previous year by the price at the end of the current month. For the months of January and February, this is computed by dividing book value at the end of two years ago by the price at the end of the current month. Data are from Amit Goyals website.
- Variance risk premium (VRP) is the difference between the risk-neutral and objective expectations of realized variance, where the risk-neutral expectation of variance is measured by VIX-squared and the realized variance is the sum of intra-daily returns of the S&P 500 index over the month. The data comes from Hao Zhou's website.

A.2. *In Cross-Sectional regressions*

- SIZE is the average of the firms market capitalization over the examination period. Following standard practice, in regressions, we take the natural logarithm to reduce skewness.
- Bid-ask spread (BAS) is the stocks average daily ratios of the difference between ask and bid quotes of over the midpoint of the bid and ask quotes over the examination period.
- Book-to-market (BM) is the average of book equity divided by market equity over the examination period.
- Illiquidity (ILLIQ) is defined for stock i as the average of the ratio of the absolute daily stock

return to its dollar trading volume over examination period (Amihud (2002)),

$$\text{ILLIQ}_{i,t} = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{\text{volume}_{i,d}\times\text{price}_{i,d}} \tag{A.1}$$

where $R_{i,d}$ is the return of stock i on day d, $\text{volume}_{i,d}$ is the daily trading volume, and $\text{price}_{i,d}$ is the daily price. We then transform the illiquidity by its natural logarithm to reduce skewness.

- Idiosyncratic volatility (IVOL) (Ang et al. (2006b))is the standard deviation of the residuals from the regression based on the daily return regression:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i^{\text{MKT}}\text{MKT}_d + \beta_i^{\text{SMB}}\text{SMB}_d + \beta_i^{\text{HML}}\text{HML}_d + \epsilon_{i,d} \tag{A.2}$$

where $R_{i,d}$ is the return of stock i on day d, $r_{f,d}$ is the risk-free rate on day d. MKT, SMB and HML are, respectively, the excess return on the market portfolio and the return on two long/short portfolios that capture size and book-to-market effects (Fama and French (1993)).

- Coskewness (CSK) of stock i at time t is estimated using daily returns as

$$\text{CSK}_{i,t} = \frac{\frac{1}{D}\sum_d (R_{i,d}-\mu_i)(\text{MKT}_d - \mu_{\text{MKT}})^2}{\sqrt{\text{var}(R_{i,d})}\text{var}(\text{MKT}_d)} \tag{A.3}$$

where μ_i is the average excess return on the stock, and D denotes the number of trading days in examination period (e.g., Harvey and Siddique (2000) and Ang et al. (2006a)).

- Cokurtosis (CKT) of stock i at time t is estimated using daily returns as

$$\text{CKT}_{i,t} = \frac{\frac{1}{D}\sum_d (R_{i,d}-\mu_i)(\text{MKT}_d - \mu_{\text{MKT}})^3}{\sqrt{\text{var}(R_{i,d})}\text{var}(\text{MKT}_d)^{3/2}} \tag{A.4}$$

where variables are the same as for CSK.

- Realized skewness (RSKEW) is the stock's skewness of daily returns over the examination period.
- Realized kurtosis (RKURT) is the stock's kurtosis of daily returns over the examination period.

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Table 1: Summary statistics for market left- and right-tail risk factors.

This table reports descriptive statistics (Panel A) and pairwise correlations (Panel B) for our measures of the market left- and right-tail risk. The sample is from January 1996 to May 2017. The LEFT (RIGHT) risk factor is the daily return on a Delta- and Vega-neutral portfolio that is only sensitive to the left (right) tail of the risk-neutral density of market returns. $\text{SKEW}^{\text{NonPar}}$ is nonparametric risk-neutral skewness defined as the the difference between the out-of-the-money call and out-of-the put implied volatilities. SKEW^{L} is left risk-neutral skewness defined as the difference between the out-of-the-money put and at-the-money put implied volatilities. SKEW^{R} is right risk-neutral skewness defined as the difference between the out-of-the-money call and at-the-money call implied volatilities. SKEW^{BKM} is risk-neutral skewness based on Bakshi et al. (2003). JUMP and VOL are jump and volatility risk factors, respectively (Cremers et al. (2015)).

Panel A: Descriptive statistics (daily)

			Percentile						
	Mean(%)	Std.dev	10th	25th	50th	75th	90th	Skew	Kurt
LEFT	-0.0236	0.3255	-0.3616	-0.1608	-0.0175	0.1174	0.2842	0.8790	12.8524
RIGT	0.0094	0.3679	-0.3474	-0.1454	0.0052	0.1712	0.3788	-0.9919	20.8863

Panel B: Correlations of different risk factors

	LEFT	RIGHT	$\Delta\text{SKEW}^{\text{NonPar}}$	$\Delta\text{SKEW}^{\text{LEFT}}$	$\Delta\text{SKEW}^{\text{RIGHT}}$	$\Delta\text{SKEW}^{\text{BKM}}$	JUMP	VOL
LEFT	1.000							
RIGHT	-0.484	1.000						
$\Delta\text{SKEW}^{\text{NonPar}}$	0.363	-0.526	1.000					
$\Delta\text{SKEW}^{\text{LEFT}}$	0.554	-0.239	-0.057	1.000				
$\Delta\text{SKEW}^{\text{RIGHT}}$	-0.512	0.571	-0.392	-0.604	1.000			
$\Delta\text{SKEW}^{\text{BKM}}$	0.013	-0.078	0.152	0.055	-0.170	1.000		
JUMP	-0.069	-0.089	-0.204	0.132	-0.124	0.014	1.000	
VOL	0.119	0.098	-0.182	0.281	-0.049	0.026	-0.176	1.000

Table 2: Forecast regressions for aggregate market return.

This table reports result from forecasting regressions of S&P 500 index one-month returns. The sample extends from January 1996 to May 2017. Following the literature on equity premium forecasting (e.g., Bollerslev et al. (2009), Welch and Goyal (2008), Kelly and Jiang (2014), among others), we use monthly data and aggregate our daily returns on LEFT and RIGHT strategies to monthly returns. Control variables are obtained from Amit Goyal's and Hao Zhou's Web sites. To illustrate economic magnitudes, all reported predictive coefficients are scaled to be interpreted as the effect of a two-standard-deviation increase in the forecasting variables on future annualized returns.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
LEFT	-22.912		-25.496		-23.927		-26.708			-21.856		-15.440		-17.878
	(-3.572)		(-3.904)		(-3.826)		(-4.380)			(-3.144)		(-2.239)		(-2.265)
RIGHT		19.498		20.569		19.839		21.469			18.185		13.257	12.014
		(1.970)		(2.129)		(1.997)		(2.293)			(1.906)		(1.579)	(1.122)
BM			13.222	10.368										
			(2.420)	(1.891)										
E/P					7.783	5.830								
					(0.666)	(0.561)								
D/P							18.811	16.062						
							(2.212)	(2.034)						
SVAR										-5.864	-4.568			
										(-0.805)	(-0.728)			
VRP									23.565			16.631	19.269	
									(4.480)			(2.748)	(2.673)	
adj. R^2	4.620	3.244	5.862	3.890	4.824	3.196	7.505	5.306	4.912	4.572	3.055	6.367	6.053	5.393

Table 3: Pairwise correlations of the factor loadings.
This table reports time-series means of pairwise correlations for risk factor betas. The sample is from January 1996 to May 2017. Betas are estimated monthly using daily returns over rolling annual periods based on Equation (3). $SKEW^{BKM}$ is risk-neutral skewness based on Bakshi et al. (2003). JUMP and VOL are jump and volatility risk factors, respectively (Cremers et al. (2015)).

	LEFT	RIGHT	$SKEW^{BKM}$	JUMP	VOL
LEFT	1.000				
RIGHT	-0.556	1.000			
$SKEW^{BKM}$	0.094	-0.181	1.000		
JUMP	-0.006	-0.184	-0.029	1.000	
VOL	0.064	-0.015	0.011	-0.261	1.000

Table 4: Portfolio characteristics sorted by betas.

This table reports time-series averages of value-weighted characteristics of stocks sorted by β_{LEFT} (Panel A) and β_{RIGHT} (Panel B). Betas are estimated monthly using daily returns over rolling annual periods based on Equation (3). All reported portfolio characteristics are contemporaneous with the betas used to form the portfolio. The sample is from January 1996 to May 2017. β_{MKT}, β_{SMB}, and β_{HML} are Fama-French three-factor betas. SIZE represents firms size defined as the logarithm of the market capitalization of firms. BM denotes the ratio of the book value of common equity to the market value of equity. BAS is the stocks average daily ratios of the difference between ask and bid quotes to the midpoint of the bid and ask quotes over the examination period. ILLIQ refers to the logarithm of the average daily ratio of the absolute stock return to the dollar trading volume over the examination period. MAX is the maximum daily return over the examination period. IVOL denotes idiosyncratic volatility. RSKEW and RKURT represent realized skewness and the realized kurtosis, respectively. CSK and CKT are measures of coskewness and cokurtosis, respectively.

Quintile	β_{LEFT}	β_{RIGHT}	β_{MKT}	β_{SMB}	β_{HML}	β_{JUMP}	β_{VOL}	SIZE	BM	BAS	ILLIQ	MAX	IVOL	RSKEW	RKURT	CSK	CKT
Panel A: Sorted by β_{LEFT}																	
1 (Low)	-0.652	0.350	1.059	0.036	-0.135	0.925	-0.011	16.889	0.391	0.334	-15.957	7.142	1.870	0.118	6.235	-0.092	2.591
2	-0.197	0.078	0.966	-0.065	-0.010	0.541	-0.018	17.268	0.399	0.315	-16.293	5.592	1.470	0.077	4.372	-0.092	2.679
3	0.076	-0.064	0.958	-0.051	0.020	0.372	-0.002	17.244	0.402	0.300	-16.265	5.520	1.452	0.082	4.142	-0.098	2.657
4	0.358	-0.201	1.011	0.033	0.080	0.554	0.026	16.914	0.421	0.308	-15.968	6.146	1.626	0.098	4.657	-0.093	2.575
5 (High)	0.886	-0.445	1.131	0.279	0.153	1.054	0.080	16.317	0.425	0.319	-15.365	7.927	2.152	0.131	7.122	-0.089	2.303
Panel B: Sorted by β_{RIGHT}																	
1 (Low)	0.444	-0.706	1.078	0.100	0.082	2.756	0.029	16.683	0.419	0.331	-15.722	7.351	1.948	0.152	6.162	-0.052	2.425
2	0.137	-0.260	0.985	-0.073	0.041	0.993	-0.002	17.261	0.406	0.301	-16.291	5.696	1.486	0.087	4.250	-0.082	2.667
3	-0.009	-0.006	0.949	-0.081	0.012	0.135	-0.011	17.326	0.401	0.295	-16.348	5.392	1.427	0.071	4.019	-0.103	2.701
4	-0.151	0.251	0.977	-0.034	-0.014	-0.644	-0.013	17.174	0.402	0.310	-16.190	5.783	1.535	0.087	4.770	-0.119	2.669
5 (High)	-0.402	0.727	1.097	0.138	-0.065	-0.944	0.018	16.658	0.397	0.328	-15.778	7.748	2.032	0.108	6.579	-0.122	2.553

Table 5: Univariate portfolio sorts based on the market left- and right-tail risk betas.
This table reports the results of univariate portfolio sorts based on β_{LEFT} (Panel A) and β_{RIGHT} (Panel B). Betas are estimated monthly using daily returns over rolling annual periods based on Equation (3). We value-weight stocks in each quintile portfolio and rebalance them monthly. The sample is from January 1996 to May 2017. For each quintile of factor betas, the rows report the average raw returns, the CAMP, 3-factor Fama and French (1993), 4-factor Carhart (1997) and 5-factor Pástor and Stambaugh (2003) alphas. The column high-low reports the difference in average raw and risk-adjusted returns between high betas and low betas quintiles. Because we use overlapping returns and beta estimates, we adjust standard errors accordingly using 12 Newey-West lags.

Rank	1 (Low)	2	3	4	5 (High)	High - Low
			Panel A: Quintile portfolios of stocks sorted by β_{LEFT}			
Average return	13.913	11.749	10.975	9.596	7.265	-6.648
	(3.697)	(4.300)	(3.909)	(2.964)	(1.655)	(-2.462)
CAPM alpha	4.777	5.150	4.232	1.841	-2.529	-7.305
	(2.200)	(4.822)	(2.094)	(0.478)	(-2.257)	(-2.575)
3-factor alpha	5.853	5.186	3.785	0.954	-3.835	-9.688
	(4.171)	(6.122)	(2.356)	(1.538)	(-2.806)	(-3.670)
4-factor alpha	5.494	4.965	2.975	0.624	-5.306	-10.800
	(3.836)	(6.483)	(1.941)	(1.283)	(-2.844)	(-3.360)
5-factor alpha	6.402	4.351	3.538	1.548	0.246	-6.155
	(3.920)	(3.387)	(1.207)	(1.073)	(0.786)	(-1.739)
			Panel B: Quintile portfolios of stocks sorted by β_{RIGHT}			
Average return	6.413	10.977	11.834	12.321	14.160	7.747
	(1.764)	(3.815)	(4.385)	(4.302)	(3.341)	(3.747)
CAPM alpha	-2.303	4.410	5.296	5.101	3.873	6.176
	(-1.790)	(3.222)	(5.462)	(6.789)	(2.816)	(2.973)
3-factor alpha	-2.892	4.032	4.844	4.891	4.422	7.314
	(-2.013)	(3.887)	(10.629)	(7.602)	(2.676)	(3.001)
4-factor alpha	-2.737	3.137	4.613	4.350	2.929	5.666
	(-1.713)	(3.721)	(10.564)	(7.440)	(2.354)	(2.469)
5-factor alpha	-1.630	4.788	4.556	4.654	6.771	8.401
	(-0.919)	(3.481)	(8.498)	(5.657)	(3.285)	(3.133)

Table 6: Bivariate portfolio sorts based on market left- and right-tail risk betas.
This table shows the results from unconditional (Panel A) and conditional (Panels B and C) double-sorted portfolios. In Panel A, quintile portfolios are formed by independently sorting β_{LEFT} and β_{RIGHT}. In Panel B, quintile portfolios are first formed by sorting the stocks based on β_{RIGHT}. Then, within each β_{RIGHT}, stocks are sorted into quintile portfolios ranked by β_{LEFT}. Panel C performs a similar dependent sort procedure but first sequentially sorts on β_{LEFT} and then on β_{RIGHT}. In Panels B and C, Return diff. reports the average raw return difference between high β_{LEFT} (β_{RIGHT}) and low β_{LEFT} (β_{RIGHT}) quintile portfolios after contronlling for β_{RIGHT} (β_{LEFT}). FFC4 alpha reports the 4-factor alpha Carhart (1997).

Panel A: Quintile portfolios of stocks independently sorted by β_{LEFT} and β_{RIGHT}

		β_{RIGHT}						
		1 (Low)	2	3	4	5 (High)	High - Low	t-stat
β_{LEFT}	1 (Low)	10.621	12.881	13.377	14.263	15.456	4.835	2.218
	2	10.296	12.853	12.497	11.993	12.608	2.312	1.587
	3	9.340	11.533	11.654	12.101	13.089	3.749	2.234
	4	7.457	10.957	11.279	10.068	11.776	4.319	2.769
	5 (High)	5.754	8.537	10.267	12.704	11.635	5.881	2.327
	High - Low	-4.867	-4.344	-3.111	-1.560	-3.822		
	t-stat	-1.865	-2.278	-1.545	-0.546	-1.386		

Panel B: Quintile portfolios of stocks sorted by LEFT controlling for RIGHT

		β_{LEFT}						
		1 (Low)	2	3	4	5 (High)	High - Low	t-stat
β_{RIGHT}	1 (Low)	7.711	8.130	7.270	6.634	5.323	-2.388	-0.501
	2	11.799	11.980	11.541	10.769	8.371	-3.429	-1.583
	3	13.200	11.893	11.931	12.094	9.939	-3.262	-1.667
	4	14.772	12.465	11.273	12.215	10.426	-4.347	-2.002
	5 (High)	18.326	15.210	13.760	13.648	10.584	-7.742	-1.841
						Return diff.	-4.233	-1.690
						FFC4 alpha	-4.294	-1.758

Panel C: Quintile portfolios of stocks sorted by RIGHT controlling for LEFT

		β_{RIGHT}						
		1 (Low)	2	3	4	5 (High)	High - Low	t-stat
β_{LEFT}	1 (Low)	11.160	13.080	14.738	17.010	19.108	7.949	3.226
	2	11.323	12.365	12.127	12.470	12.301	0.979	0.798
	3	10.497	11.819	11.358	11.603	13.304	2.806	2.208
	4	7.546	10.287	11.020	11.038	10.010	2.464	2.218
	5 (High)	4.408	6.523	8.232	9.169	10.365	5.957	4.367
						Return diff.	4.031	3.581
						FFC4 alpha	3.925	3.571

Table 7: Fama-MacBeth cross-sectional regressions.

This table reports the results of series of firm-level Fama-MacBeth regressions. Every month, we run cross-sectional regressions of 12-month excess returns on contemporaneous realized tail factors betas and various control variables which include market beta (BETA), log market capitalization (SIZE), book-to-market ratio (BM), relative bid-ask spread (BAS), illiquidity (ILLIQ), Jump risk (JUMP), coskewness (CSK), cokurtosis (CKT), realized skewness (RSKEW) and realized kurtosis (RKURT). The LEFT (RIGHT) risk factor is the daily return on a Delta- and Vega-neutral portfolio that is only sensitive to the left (right) tail of the risk-neutral density of market returns. The Newey and West (1987) t-statistics of each average slope coefficients are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Constant	0.136	0.134	0.137	0.130	0.145	0.137	0.136	0.134	0.136	0.182	0.184	0.188	0.121	0.119	0.122	0.083
	(4.083)	(4.169)	(4.275)	(2.233)	(2.525)	(2.400)	(4.295)	(4.335)	(4.396)	(4.572)	(4.743)	(4.819)	(3.672)	(3.744)	(3.867)	(1.081)
LEFT		-0.028	-0.016		-0.026	-0.018		-0.025	-0.017		-0.034	-0.026		-0.028	-0.017	-0.006
		(-2.000)	(-0.993)		(-2.431)	(-1.447)		(-2.272)	(-1.661)		(-2.758)	(-1.769)		(-1.970)	(-1.029)	(-0.586)
RIGHT	0.034		0.026	0.028		0.019	0.028		0.021	0.035		0.021	0.034		0.026	0.023
	(3.410)		(2.267)	(3.660)		(2.289)	(2.375)		(2.144)	(3.485)		(2.157)	(3.423)		(2.371)	(2.038)
BETA	0.057	0.063	0.059	0.063	0.068	0.063	0.059	0.064	0.061	0.097	0.106	0.103	0.060	0.067	0.062	0.099
	(1.138)	(1.326)	(1.253)	(1.643)	(1.851)	(1.756)	(1.241)	(1.396)	(1.344)	(1.825)	(2.080)	(2.048)	(1.263)	(1.467)	(1.384)	(2.003)
SIZE				0.026	0.025	0.026										0.031
				(3.784)	(3.585)	(3.661)										(3.157)
BM				0.063	0.061	0.062										0.049
				(4.882)	(4.678)	(4.811)										(3.186)
BAS				-0.032	-0.032	-0.031										-0.079
				(-2.162)	(-2.205)	(-2.163)										(-4.225)
ILLIQ				0.030	0.029	0.030										0.027
				(4.527)	(4.542)	(4.584)										(3.765)
JUMP							-0.004	-0.004	-0.004							-0.004
							(-2.593)	(-3.227)	(-2.523)							(-2.590)
CSK										-0.159	-0.164	-0.150				-0.138
										(-1.712)	(-1.885)	(-1.712)				(-2.775)
CKT										-0.056	-0.060	-0.060				-0.049
										(-2.280)	(-2.464)	(-2.455)				(-1.942)
RKURT													-0.004	-0.004	-0.004	-0.004
													(-6.942)	(-6.913)	(-6.914)	(-7.479)
RSKEW													0.124	0.125	0.124	0.121
													(16.805)	(16.831)	(16.801)	(16.931)

Table 8: Average returns of stocks sorted by past factor loadings.
This table reports the results of univariate portfolio sorts based on β_{LEFT} and β_{RIGHT}. Betas are estimated monthly using daily returns over rolling annual periods based on Equation (3). The LEFT (RIGHT) risk factor is the daily return on a Delta- and Vega-neutral portfolio that is only sensitive to the left (right) tail of the risk-neutral density of market returns. At the beginning of each month, we form quintile portfolios based on the betas with respect to market left- or right-tail risk. Each month, we set up new 12-month portfolios. The sample is from January 1996 to May 2017. For each quintile of factor betas, the rows report the average raw returns, the CAMP, 3-factor Fama and French (1993), 4-factor Carhart (1997) and 5-factor Pástor and Stambaugh (2003) alphas. The column high-low reports the difference in average raw and risk-adjusted returns between high betas and low betas quintiles. Because we use overlapping returns and beta estimates, we adjust standard errors accordingly using 12 Newey-West lags. Panel A (B) reports results from regressions in which future LEFT (RIGHT) betas are dependent variable.

Rank	1 (Low)	2	3	4	5 (High)	High - Low
Panel A: Quintile portfolios of stocks sorted by $\beta_{LEFT}(t-12)$						
Average return	10.533	10.327	10.422	10.735	10.857	0.323
	(3.498)	(3.613)	(3.460)	(3.309)	(2.687)	(0.185)
CAPM alpha	1.655	1.631	1.440	1.240	-0.300	-1.955
	(2.373)	(1.920)	(2.554)	(2.077)	(-0.242)	(-1.212)
3-factor alpha	1.196	1.092	1.537	1.329	-0.475	-1.671
	(1.723)	(1.864)	(3.076)	(2.656)	(-0.334)	(-1.012)
4-factor alpha	0.965	1.078	1.603	1.529	-0.491	-1.456
	(1.266)	(2.146)	(3.455)	(2.555)	(-0.383)	(-0.915)
5-factor alpha	1.030	0.472	0.693	1.089	1.643	0.613
	(1.738)	(0.593)	(1.083)	(1.966)	(1.018)	(0.352)
Panel B: Quintile portfolios of stocks sorted by $\beta_{RIGHT}(t-12)$						
Average return	11.023	9.644	10.547	9.484	11.048	0.026
	(3.186)	(3.084)	(3.682)	(3.330)	(3.126)	(0.019)
CAPM alpha	1.227	0.529	1.937	0.787	0.760	-0.466
	(1.295)	(0.765)	(2.453)	(1.280)	(0.746)	(-0.344)
3-factor alpha	1.173	0.732	1.669	0.421	0.289	-0.884
	(1.323)	(1.227)	(3.247)	(0.906)	(0.267)	(-0.707)
4-factor alpha	0.717	0.338	1.558	0.593	0.799	0.081
	(0.948)	(0.634)	(3.229)	(1.426)	(0.778)	(0.068)
5-factor alpha	2.505	1.082	0.443	-0.707	0.439	-2.066
	(2.435)	(1.428)	(0.602)	(-1.019)	(0.317)	(-1.124)

Table 9: Predicting future market left- and right-tail risk loadings.
This table reports the results of Fama-MacBeth regressions in which we regress market tail risk betas estimated over $(t, t+11)$ on firm characters known at t and past factor betas estimated over $(t-12, t-1)$. The firm characteristics include market beta (BETA), log market capitalization (SIZE), book-to-market ratio (BM), relative bid-ask spread (BAS), illiquidity (ILLIQ), Jump risk (JUMP), coskewness (CSK), cokurtosis (CKT), realized skewness (RSKEW) and realized kurtosis (RKURT). The LEFT (RIGHT) risk factor is the daily return on a Delta- and Vega-neutral portfolio that is only sensitive to the left (right) tail of the risk-neutral density of market returns. The Newey and West (1987) t-statistics of each average slope coefficients are reported in parentheses.

	Panel A: Predicting β_{LEFT}			Panel B: Predicting β_{RIGHT}		
	(1)	(2)	(3)	(1)	(2)	(3)
Constant	0.091	0.089	0.461	0.003	-0.003	-0.033
	(2.899)	(2.869)	(2.838)	(0.153)	(-0.174)	(-0.294)
$\beta_{RIGHT}(t-12)$		0.010	-0.009	0.011	0.022	0.019
		(0.735)	(-0.924)	(1.124)	(1.390)	(1.546)
$\beta_{LEFT}(t-12)$	0.040	0.041	0.003		0.012	0.017
	(4.552)	(4.059)	(0.299)		(0.790)	(1.665)
BETA$(t-12)$			0.184			-0.005
			(4.047)			(-0.169)
SIZE$(t-12)$			0.006			-0.019
			(0.469)			(-1.684)
BM$(t-12)$			-0.004			-0.033
			(-0.308)			(-1.503)
BAS$(t-12)$			-0.102			0.041
			(-3.175)			(1.199)
ILLIQ$(t-12)$			0.023			-0.011
			(2.164)			(-0.963)
$\beta_{JUMP}(t-12)$			0.002			-0.011
			(0.479)			(-3.490)
CSK$(t-12)$			-0.337			-0.430
			(-1.658)			(-2.341)
CKT$(t-12)$			-0.150			0.078
			(-6.073)			(2.835)
RSKEW$(t-12)$			-0.003			0.001
			(-3.118)			(2.038)
RKURT$(t-12)$			0.005			0.005
			(1.050)			(1.411)

Table 10: Equity portfolio analysis.
This table reports the results of univariate (Panel A) and conditional bivariate (Panel B) portfolio sorts based on β_{LEFT} and β_{RIGHT}. Different from Table 5, we use equity portfolio as test assets. Specifically, for each of the 49-industry portfolios and 100 portfolios (10×10 bivariate) formed on size and book-to-market, size and investment, and size and profitability (total of 349 portfolios), we first estimate the risk factor betas based on Equation (3). We then form quintile portfolios for the period January 1996-May 2017. For each quintile of factor betas, the rows report the average raw returns, the CAMP, 3-factor Fama and French (1993), 4-factor Carhart (1997) and 5-factor Pástor and Stambaugh (2003) alphas. The column high-low reports the difference in average raw and risk-adjusted returns between high betas and low betas quintiles. Because we use overlapping returns and beta estimates, we adjust standard errors accordingly using 12 Newey-West lags.

Panel A: Univariate portfolio sorts						
Rank	1 (Low)	2	3	4	5 (High)	High - Low
Panel A.1: Quintile portfolios of stocks sorted by β_{LEFT}						
Average return	13.079	13.245	12.803	12.707	11.682	-1.398
	(4.543)	(4.449)	(4.227)	(4.136)	(3.340)	(-1.021)
CAPM alpha	3.613	3.775	3.298	3.020	1.015	-2.598
	(1.833)	(1.668)	(1.472)	(1.406)	(0.527)	(-1.692)
3-factor alpha	1.321	0.826	0.291	0.046	-1.635	-2.957
	(1.267)	(1.153)	(0.738)	(0.137)	(-2.169)	(-1.832)
4-factor alpha	1.715	0.951	0.311	-0.084	-2.199	-3.914
	(1.335)	(1.236)	(0.862)	(-0.265)	(-2.581)	(-1.911)
5-factor alpha	0.334	-0.187	0.084	0.225	-0.386	-0.720
	(0.281)	(-0.230)	(0.171)	(0.536)	(-0.371)	(-0.363)
Panel A.2: Quintile portfolios of stocks sorted by β_{RIGHT}						
Average return	10.925	12.340	12.879	13.564	13.806	2.881
	(3.576)	(4.122)	(4.268)	(4.435)	(4.201)	(2.771)
CAPM alpha	1.080	2.782	3.307	3.974	3.577	2.497
	(0.651)	(1.317)	(1.523)	(1.767)	(1.671)	(2.423)
3-factor alpha	-1.361	-0.024	0.395	0.958	0.883	2.244
	(-3.551)	(-0.059)	(0.840)	(1.983)	(0.918)	(2.224)
4-factor alpha	-1.126	-0.182	0.378	0.858	1.265	2.391
	(-2.696)	(-0.471)	(0.872)	(1.788)	(0.749)	(2.350)
5-factor alpha	-1.716	-0.215	0.076	0.630	1.301	3.017
	(-4.101)	(-0.423)	(0.132)	(1.136)	(1.217)	(2.494)

Table 10: Continued.

Panel B: Bivariate portfolio sorts								
Panel B.1: Quintile Portfolios of Stocks Sorted by LEFT Controlling for RIGHT								
		β_{LEFT}						
		1 (Low)	2	3	4	5 (High)	High - Low	t-stat
	1 (Low)	11.177	11.840	11.173	10.841	9.596	-1.580	-0.759
	2	12.554	12.331	12.247	12.168	12.399	-0.155	-0.118
β_{RIGHT}	3	12.481	13.037	12.697	12.889	13.278	0.797	0.557
	4	12.897	13.711	13.760	14.027	13.450	0.553	0.370
	5 (High)	14.061	13.462	13.205	14.487	13.817	-0.245	-0.129
						Return diff.	-0.126	-0.083
						FFC4 alpha	-0.102	-0.066
Panel B.2: Quintile Portfolios of Stocks Sorted by RIGHT Controlling for LEFT								
		β_{RIGHT}						
		1 (Low)	2	3	4	5 (High)	High - Low	t-stat
	1 (Low)	12.080	12.801	12.945	12.751	14.819	2.739	2.132
	2	12.179	12.721	13.729	13.635	13.994	1.816	1.505
β_{LEFT}	3	11.504	12.058	13.158	13.450	13.874	2.370	2.007
	4	11.300	12.444	12.691	13.108	13.984	2.684	2.124
	5 (High)	9.759	10.479	11.839	13.012	13.320	3.561	2.279
						Return diff.	2.634	2.230
						FFC4 alpha	2.357	2.160

Table 11: Mutual Funds analysis.
This table reports the results of univariate (Panel A) and conditional bivariate (Panel B) portfolio sorts based on β_{LEFT} and β_{RIGHT}. Different from Table 5, we use mutual funds as test assets. To do so, we collect a sample of mutual funds from the CRSP Survivor Bias Free U.S. Mutual Fund Database. We first estimate the risk factor betas based on Equation (3). We then form quintile portfolios for the period January 1996-May 2017. High-Low represents the difference in average raw returns between high betas and low betas quintiles. Because we use overlapping returns and beta estimates, we adjust standard errors accordingly using 12 Newey-West lags.

Panel A: Univariate portfolio sorts		
	β_{LEFT}	β_{RIGHT}
1 (Low)	7.767	6.213
	(2.617)	(1.774)
2	7.182	7.277
	(2.441)	(2.354)
3	7.273	7.342
	(2.427)	(2.434)
4	7.759	7.905
	(2.370)	(2.547)
5 (High)	7.589	8.834
	(1.858)	(2.587)
High - Low	-0.178	2.621
	(-0.090)	(2.672)

Table 11: Continued.

Panel B: Bivariate portfolio sorts								
Panel B.1: Quintile Portfolios of Stocks Sorted by LEFT Controlling for RIGHT								
		β_{LEFT}						
		1 (Low)	2	3	4	5 (High)	High - Low	t-stat
	1 (Low)	6.453	6.621	6.524	6.555	4.909	-1.544	-0.604
	2	6.722	6.855	6.852	7.513	8.442	1.720	0.967
β_{RIGHT}	3	6.719	6.680	6.694	7.588	9.026	2.307	1.377
	4	7.470	7.003	7.336	8.267	9.447	1.977	1.184
	5 (High)	9.210	7.918	8.105	8.737	10.191	0.981	0.370
						Return diff.	1.088	0.599
Panel B.2: Quintile Portfolios of Stocks Sorted by RIGHT Controlling for LEFT								
		β_{RIGHT}						
		1 (Low)	2	3	4	5 (High)	High - Low	t-stat
	1 (Low)	6.876	7.209	7.554	8.055	9.138	2.262	1.172
	2	7.123	6.859	6.440	6.964	8.523	1.400	1.756
β_{LEFT}	3	6.636	6.782	6.733	7.289	8.920	2.284	2.927
	4	6.327	7.121	7.583	8.272	9.493	3.166	2.994
	5 (High)	4.016	6.661	8.065	9.155	10.050	6.034	3.911
						Return diff.	3.029	3.653

Table 12: Univariate portfolio sorts based on market bi-tail risk betas.
This table reports the results of univariate portfolio sorts based on $\beta_{\text{Bi-Tail}}$ (Panel A) and $\beta_{\text{SKEW}^{\text{BKM}}}$ (Panel B). The Bi-Tail risk factor is the daily return on a Delta- and Vega-neutral portfolio that is sensitive to both the left and right tails of the risk-neutral density of market returns. SKEW^{BKM} is risk-neutral skewness based on Bakshi et al. (2003). Betas are estimated monthly using daily returns over rolling annual periods based on Equation (3). We value-weight stocks in each quintile portfolio and rebalance them monthly. The sample is from January 1996 to May 2017. For each quintile of factor betas, the rows report the average raw returns, the CAMP, 3-factor Fama and French (1993), 4-factor Carhart (1997) and 5-factor Pástor and Stambaugh (2003) alphas. The column high-low reports the difference in average raw and risk-adjusted returns between high betas and low betas quintiles. Because we use overlapping returns and beta estimates, we adjust standard errors accordingly using 12 Newey-West lags.

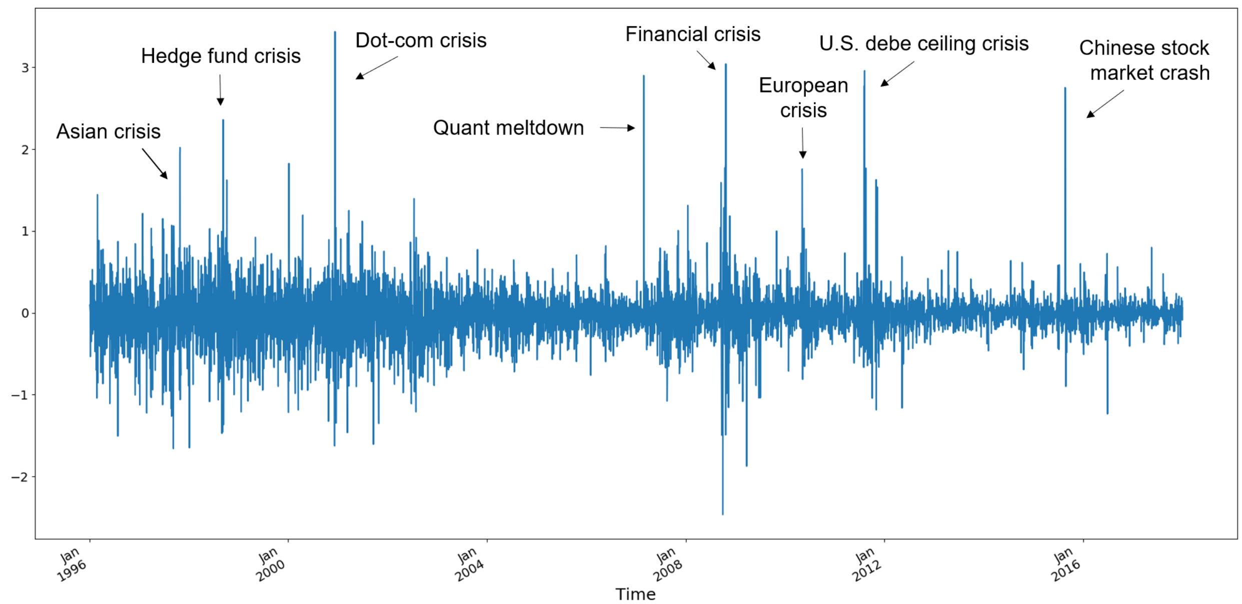
Rank	1 (Low)	2	3	4	5 (High)	High - Low
	Panel A: Quintile portfolios of stocks sorted by $\beta_{\text{Bi-Tail}}$					
Average return	8.055	9.598	11.166	12.397	13.180	5.124
	(2.045)	(3.193)	(4.084)	(4.101)	(3.078)	(1.554)
CAPM alpha	-0.651	2.562	4.626	4.855	3.040	3.690
	(-0.286)	(1.869)	(4.483)	(7.195)	(1.636)	(1.002)
3-factor alpha	-1.099	1.860	4.086	4.496	3.554	4.653
	(-0.411)	(1.810)	(7.715)	(8.741)	(2.122)	(1.237)
4-factor alpha	-3.337	1.114	3.618	4.712	3.984	7.321
	(-1.351)	(0.933)	(5.868)	(9.326)	(2.580)	(2.079)
5-factor alpha	-0.298	1.292	3.781	4.624	6.000	6.298
	(-0.097)	(1.145)	(5.918)	(6.348)	(3.068)	(1.467)
	Panel B: Quintile portfolios of stocks sorted by $\beta_{\text{SKEW}^{\text{BKM}}}$					
Average return	9.860	11.092	11.683	11.481	13.239	3.379
	(2.966)	(4.169)	(4.019)	(3.398)	(2.731)	(1.213)
CAPM alpha	2.020	4.774	4.629	3.067	1.726	-0.294
	(1.880)	(4.114)	(3.953)	(4.419)	(0.893)	(-0.126)
3-factor alpha	1.882	4.288	4.378	3.018	1.655	-0.227
	(1.428)	(6.273)	(5.179)	(4.296)	(0.744)	(-0.085)
4-factor alpha	1.391	4.057	3.472	2.705	-0.143	-1.534
	(0.994)	(5.884)	(6.260)	(4.234)	(-0.086)	(-0.653)
5-factor alpha	1.877	3.522	3.389	3.064	6.210	4.333
	(1.170)	(4.464)	(2.773)	(3.239)	(2.458)	(1.432)

Table 13: Fama-MacBeth cross-sectional regressions with alternative downward jump risk proxies.

This table reports the results of a series of firm-level Fama-MacBeth regressions with alternative downward jump risk measures. The RIGHT (LEFT) risk factor is the daily return on a Delta- and Vega-neutral portfolio that is only sensitive to the right (left) tail of the risk-neutral density of market returns. IV-Slope is the difference between the implied volatility of an out-of-the-money put option (-0.2 Delta) and an at-the-money call option (0.5 Delta) Yan (2011). RIX is a rare disaster concern index defined in Gao et al. (2018). Every month, we run cross-sectional regressions of 12-month excess returns on contemporaneous realized tail factors betas and various control variables which include market beta (BETA), log market capitalization (SIZE), book-to-market ratio (BM), relative bid-ask spread (BAS), illiquidity (ILLIQ), Jump risk (JUMP), coskewness (CSK), cokurtosis (CKT), realized skewness (RSKEW) and realized kurtosis (RKURT). The Newey and West (1987) t-statistics of each average slope coefficients are reported in parentheses.

	PROXY = IV-Slope					PROXY = RIX				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Constant	0.133	0.129	0.133	0.182	0.118	0.135	0.124	0.136	0.184	0.120
	(4.077)	(2.128)	(5.569)	(4.605)	(3.666)	(4.214)	(2.076)	(5.858)	(4.752)	(3.787)
RIGHT	0.022	0.016	0.018	0.025	0.022	0.027	0.022	0.023	0.030	0.028
	(2.027)	(1.910)	(1.909)	(2.393)	(2.013)	(2.283)	(2.125)	(2.085)	(2.423)	(2.278)
PROXY	-0.039	-0.035	-0.031	-0.031	-0.039	-0.024	-0.023	-0.015	-0.021	-0.023
	(-2.084)	(-2.081)	(-1.857)	(-1.749)	(-2.021)	(-2.015)	(-2.395)	(-1.940)	(-1.773)	(-1.974)
BETA	0.061	0.066	0.061	0.099	0.065	0.059	0.066	0.058	0.099	0.064
	(1.267)	(1.677)	(1.662)	(1.920)	(1.434)	(1.241)	(1.670)	(1.579)	(1.908)	(1.388)
SIZE		0.026					0.029			
		(3.501)					(3.829)			
BM		0.063					0.064			
		(4.747)					(4.827)			
BAS		-0.031					-0.043			
		(-1.935)					(-2.763)			
ILLIQ		0.030					0.033			
		(4.258)					(4.610)			
JUMP			-0.004					-0.002		
			(-3.130)					(-2.526)		
CSK				-0.156					-0.100	
				(-1.683)					(-1.108)	
CKT				-0.056					-0.055	
				(-2.313)					(-2.265)	
RSKEW					-0.004					-0.004
					(-6.930)					(-6.886)
RKURT					0.125					0.124
					(16.805)					(17.068)

Panel A: Daily Returns on the LEFT Factor (%)



Panel B: Daily Returns on the RIGHT Factor (%)

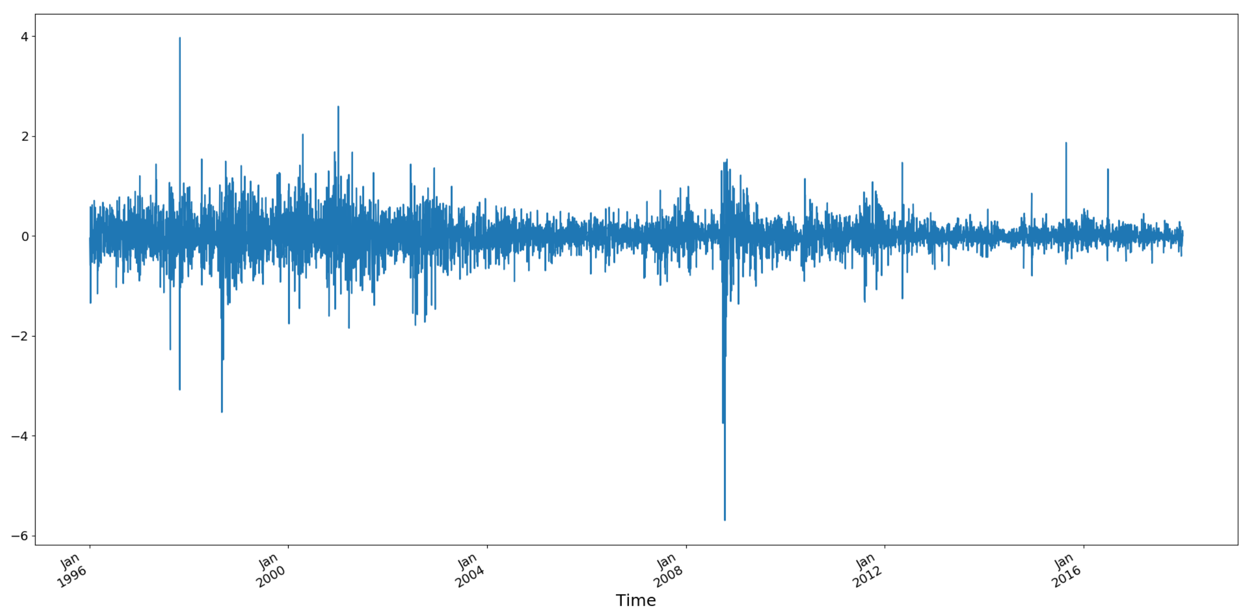
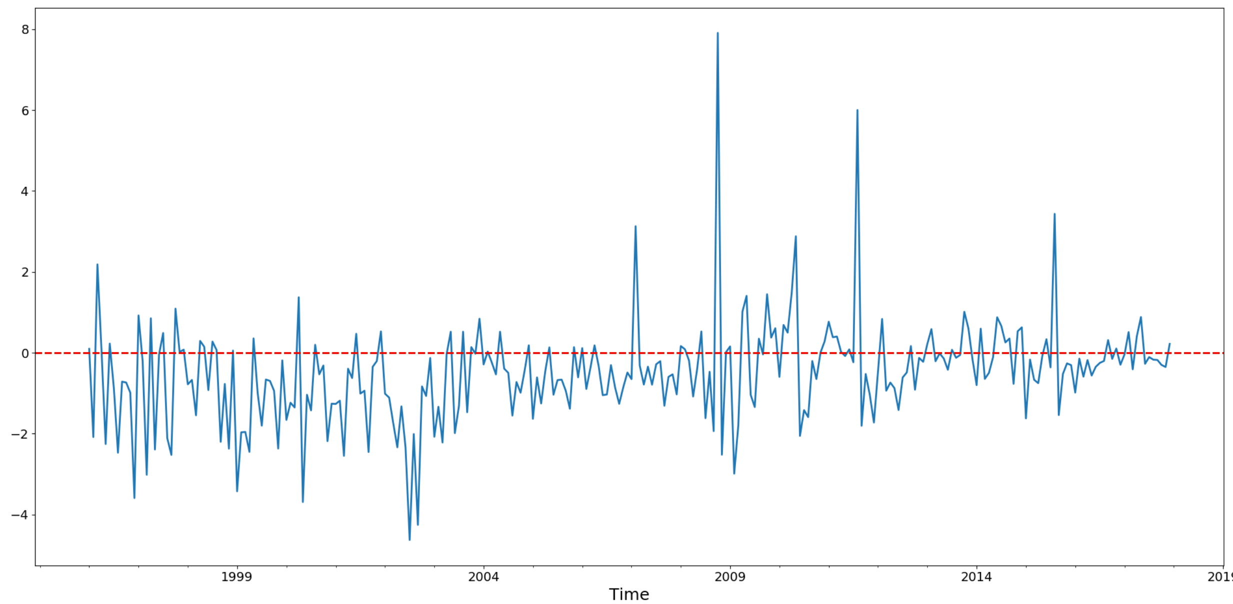


Fig. 1. Daily returns on risk factors. This figure plots the time-series of daily returns of the LEFT (Panel A) and RIGHT (Panel B) strategies from January 1996 to May 2017. The LEFT (RIGHT) strategy is constructed such that it has a positive return if the left (right) tail of the risk-neutral distribution of market return increases. The major crises during this sample period are also marked in Panel A.

Panel A: Monthly Returns on the LEFT Factor (%)



Panel B: Monthly Returns on the RIGHT Factor (%)

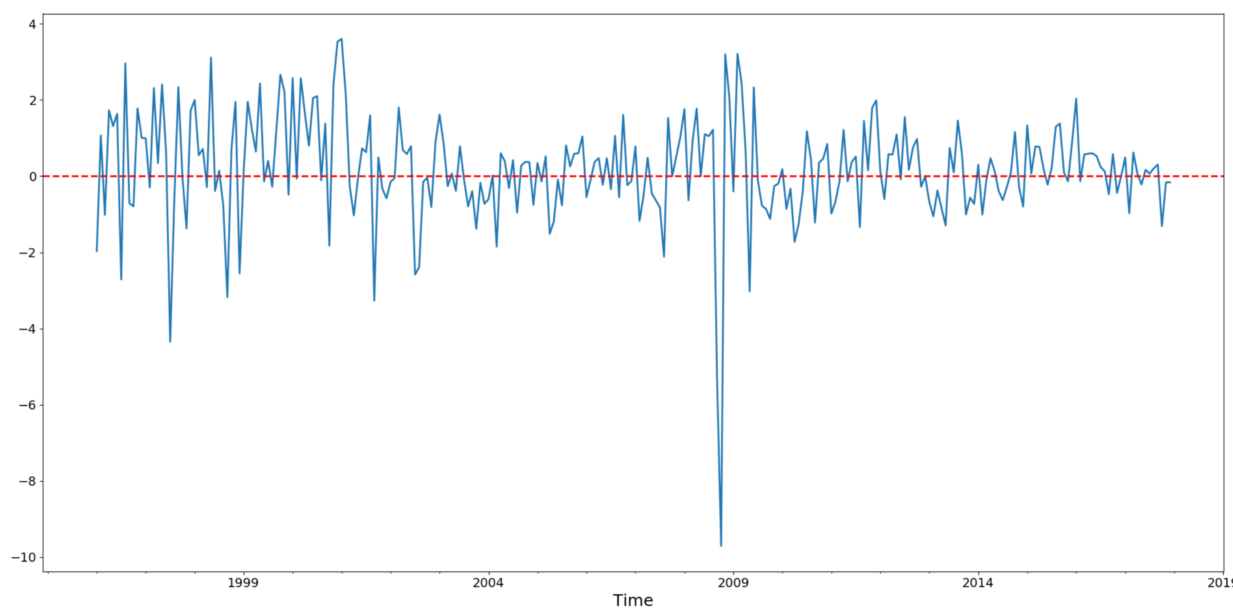


Fig. 2. Monthly returns on risk factors. This figure plots the time-series of monthly returns of the LEFT (Panel A) and RIGHT (Panel B) strategies from January 1996 to May 2017. The LEFT (RIGHT) strategy is constructed such that it has a positive return if the left (right) tail of the risk-neutral distribution of market return increases. The horizontal dashed line represents zero levels. The sample extends from January 1996 to May 2017.

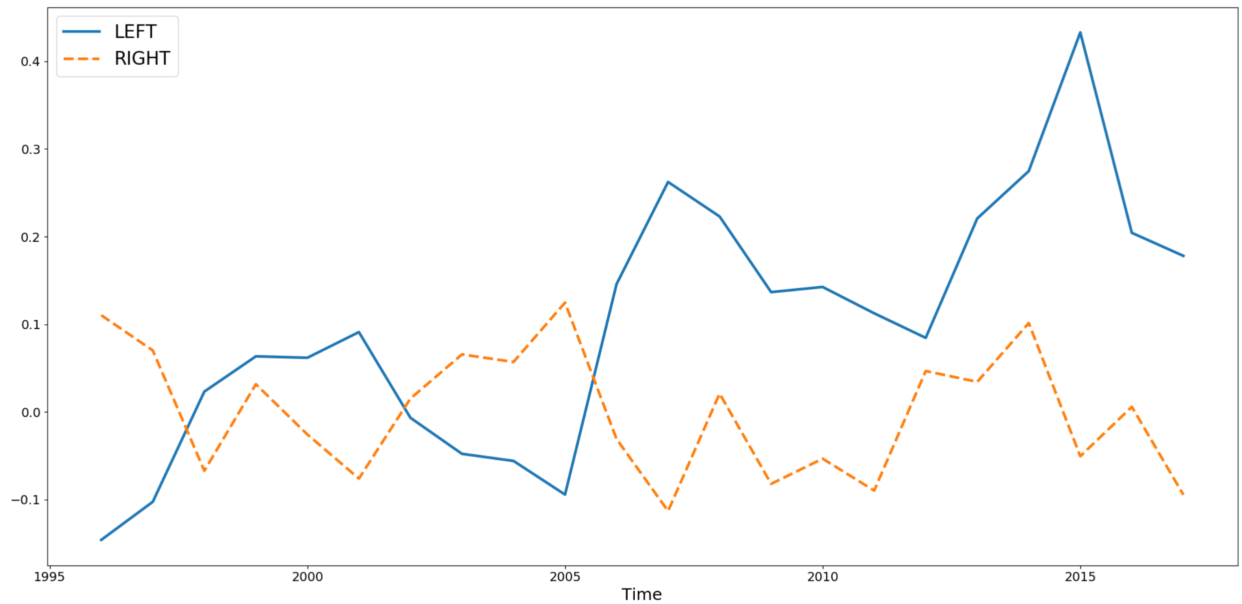


Fig. 3. Market tail risk loadings. This figure plots the time series of the cross-sectional average of market tail risk loadings. Factor betas are estimated monthly using daily returns over rolling annual periods based on Equation (3). The LEFT betas (solid line) are stocks' sensitivities to the LEFT risk factor. The RIGHT betas (dashed line) are stocks' sensitivities to the RIGHT risk factor. The RIGHT (LEFT) is the daily return on a Delta- and Vega-neutral portfolio that is only sensitive to the right (left) tail of risk-neutral density of market returns. The sample extends from January 1996 to May 2017.

Fig. 4. Cumulative returns of hedge portfolios. This figure plots the time series of cumulative returns of LEFT (solid line) and RIGHT (dashed line) risk factor hedge (value-weighted) portfolios. The RIGHT (LEFT) is the daily return on a Delta- and Vega-neutral portfolio that is only sensitive to the right (left) tail of risk-neutral density of market returns. For each month, we average the returns of all active portfolios during that month. The sample is from January 1996 to May 2017. The shaded area indicates the period marked as major crises (e.g., the Asian crisis of 2007, the Dot-com crisis in 2001, and the financial crisis in 2008).