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Is tail risk priced in the cross-section of international stock index returns?

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Abstract: This study examines the predictive power of tail risk measures in stock indices returns using a comprehensive dataset covering 50 countries from 1926 to 2021. Our findings reveal that tail risk measures exhibit predictive power when considered independently. However, their forecasting abilities disappear when other risk and return factors are incorporated. This suggests that tail risk measures do not contain incremental information about the cross-section of stock returns beyond the commonly used global factors. Our findings are robust across various considerations, holding for alternative tail risk measure types, estimation periods, and different control variables subsets.

Keywords: Tail risk; Left-tail risk; International markets; Equity returns; Cross-section of returns; Return predictability; Asset pricing; Equity anomalies; Idiosyncratic volatility.

JEL classification: G10, G12, G15.

1. Introduction

Unlike the concept of financial systemic risk, which is typically associated with banking systems (Li et al., 2019; Qin & Zhou, 2019), tail risk, also known as extreme risk, extends its relevance to individual securities, asset classes, and portfolio levels (Homescu, 2014; Long, Zhu, et al., 2019).

In this paper, we conduct an international examination of the predictive power of five tail risk measures for stock index returns. Using up to 50 equity market indices, we construct a comprehensive dataset from 1926 to 2021, allowing us to capture a broad range of market conditions and economic cycles. We apply portfolio sorts and cross-sectional regressions to determine whether tail risk measures predict future returns in the cross-section when other risk factors are incorporated into the analysis. Furthermore, we conduct sensitivity analyses to ensure our findings' robustness and explore potential variations across different model specifications and periods.

Our findings support that some tail risk measures while demonstrating predictive power in isolation, lose their explanatory power when control variables are incorporated. This is exemplified by the performance of an equal-weighted (value-weighted) long-short quintile portfolio, which buys (sells) equity indices with the highest (lowest) tail risk. Such a portfolio does not display a statistically significant mean monthly return when other factors are considered. This suggests that tail risk measures may not provide additional explanatory power for differences in stock index returns beyond what other commonly used factors capture. Furthermore, our cross-sectional regression analysis outcomes indicate that while VaR and ES measures might exhibit some predictive power when examined independently, their explanatory capacity decreases when other factors are included in the study. Lastly, our findings are robust across various considerations, holding for alternative tail risk measure types, estimation periods, and different control variables subsets.

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Our results contribute to two strains of literature. First, our study contributes to the empirical asset pricing literature on tail risk, which has previously been limited to single domestic markets (Huang et al., 2012; Kelly & Jiang, 2014; Bali et al., 2014; Long et al., 2018), equity mutual fund markets (Xiong et al., 2014), or global markets (Long, Zhu, et al., 2019). We expand this by examining the relationship between five types of tail risk and expected stock returns across 50 equity market indices. Secondly, we contribute to the literature on the cross-sectional tail-risk anomaly (Chabi-Yo et al., 2018; Atilgan et al., 2020). To our knowledge, we are the first to extend the cross-sectional tail-risk anomaly to the level of worldwide stock market indices.

Following the introduction, the structure of the remainder of this article is organized as follows: Section 2 provides a review of the relevant literature, setting the stage for our research questions. Section 3 details the sample selection process and the methodology employed in our study. In Section 4, we present and discuss our empirical findings. Finally, Finally, Section 5 concludes.

2. Literature Review

Numerous empirical studies have been dedicated to quantifying tail risk and exploring its impact on the fluctuations of stock returns. The results, however, have been varied, mainly due to the diversity in the risk measures and samples employed.

Several research papers have suggested a positive correlation between tail risk and stock returns. Bali et al. (2009) use value-at-risk, expected shortfall, and tail risk measures and find a positive and significant relation between downside risk and the portfolio returns on U.S. stocks. Similarly, Huang et al. (2012) document a significantly positive EDR (extreme downside risk) premium in the cross-section of the U.S. stock returns even after controlling for market, size, value, momentum, and liquidity effects. Xiong et al. (2014) show that the tail-risk premium in U.S. and non-U.S. equity mutual funds is economically and statistically significant - funds with higher tail risk have higher expected returns. Kelly and Jiang (2014) propose a new measure of time-varying tail risk that is directly estimable from the cross-section of returns and shows that tail risk has strong predictive power for aggregate market returns. Chen et al. (2018) suggest that downside tail risk has long memory cointegration properties; hence the underlying risk aversion behavior in an integrated market is associated with the conditional quantile ratio, the correlation of stock returns, and the cointegrating coefficient of downside risk.

Contrary to the risk-return tradeoff hypothesis, several studies have argued that tail risk is negatively related to stock returns, similar to Ang et al. (2009), who argue that around the world, stocks with recent past high idiosyncratic volatility tend to have much lower returns than stocks with recent past low idiosyncratic volatility. As an example, DiTraglia and Gerlach (2013) propose lower tail dependence (χ), a measure of the probability that a portfolio will suffer large losses given that the market does, and show that lower tail dependence generates a considerable risk premium. Long et al. (2018) suggest that the idiosyncratic tail risk is significantly negatively associated with the cross-sectional expected return in Chinese stock markets. Gao et al. (2019) show that the beta with respect to an index of global ex-ante tail risk concerns (constructed using out-of-the-money options on multiple global assets), negatively drives cross-sectional return variations across asset classes, including international equity indices, foreign currencies, and government bond futures. However, there are also viewpoints that challenge this negative correlation. For instance, Bali et al. (2014) argue that tail risk lacks the predictive power for stock returns. Furthermore, Van Oordt & Zhou (2016) suggest that the influence of tail risk on stock returns is contingent on other specific conditions. Moreover (Long, Zhu, et al., 2019) show that tail risk measure proposed by Kelly & Jiang (2014) has no pricing effect in the international markets, but measures proposed in Van Oordt and Zhou (2016) and Huang et al. (2012) has a negative relationship with future stock returns, especially in developed markets. This complex research landscape underscores the need for further investigation into the relationship between tail risk and stock returns.

Existing literature on the predictive power of tail risk measures for stock returns has primarily focused on individual stocks. Our study seeks to address these gaps by shifting the focus from individual stocks to stock market indices, providing a broader, more macro-level perspective on the predictive power of tail risk measures. We extend the geographical scope of the analysis beyond a single market, conducting an international analysis encompassing a diverse range of markets. This approach allows us to capture potential cross-market variations and commonalities in the predictive power of tail risk measures.

Our research questions derived from the aims of this study are as follows: (1) Do tail risk measures possess predictive power for stock index returns when considered independently? (2) Does the explanatory power of tail risk measures persist when other risk and return factors are incorporated into the analysis? (3) Do tail risk measures provide additional explanatory power for differences in stock index returns beyond what other commonly used risk and return factors capture? How robust are these findings across different model specifications and periods?

In terms of contribution, our study enriches the debate on the predictive power of tail risk measures in two significant ways. First, by focusing on stock market indices rather than individual stocks, we offer a more holistic view of the role of tail risk measures in predicting stock market returns. Second, our international analysis extends the applicability of the findings, providing more globally relevant insights. Furthermore, our robustness checks across different model specifications and periods contribute to the reliability and generalizability of the results.

3. Data and Methods

3.1. Research Sample

Our empirical analysis relies on data from 50 stock market indices. The set includes both emerging and developed markets, including the following countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Croatia, Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea (Republic of), Latvia, Lithuania, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Philippines, Poland, Portugal, Romania, Russian Federation, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, United States, and Vietnam

The overall study period spanning from February 1926 to March 2021. The specific start dates vary across countries, as dictated by data availability. We Datastream Global Market Indixes which we spline with Global Financial Data before their inception. We used monthly total stock index returns in our analysis, and all market data is expressed in US dollars. A total of 35 454 returns for 50 markets were used.

3.2. Tail Risk Measures

In response to the significant challenge of accurately measuring tail risk, we employ four key risk measures widely recognized in the literature:

1. **Value-at-Risk and Expected Shortfall** computed using a rolling window of the past 60 months (VaR_{60} and ES_{60}). The computation of these measures follows the methodology outlined by Atilgan et al. (2020).
2. **Tail Beta (Tail β),** computed using a rolling window of the past 120 months, follows the methodology outlined by Van Oordt & Zhou (2016) and Long, Zaremba, et al. (2019)
3. **Extreme Downside Hedge (*EDH^{GJR}_{120}*)** computed using a rolling window of the past 120 months, we rely on the method of Harris et al. (2019).
4. **Idiosyncratic Tail Risk ($IDIO_{TR}$)** computed using a rolling window of the past 120 months, as described by Long et al. (2018), Huang et al. (2012), Long, Zhu, et al. (2019)

The measures are computed using historical data over varying time windows. Each of these measures provides a unique perspective on the tail risk of investments, and together they provide a comprehensive view of the risk profile of the assets under consideration.

2.3. Time-Series Tests

We sort the stock market indices into quintiles based on their tail risk measures. These quintiles are formed at the end of each preceding month. Subsequently, we construct long-short strategies involving taking a long position in the stock market indices that exhibit the highest tail risk measures and a short position in those with the lowest. The returns of these portfolios are then computed, employing either an equal-weighted or value-weighted approach, to assess the performance of our strategies. In conducting a one-way sort, at least ten countries must present valid values for the tail risk measures at each date. We term these portfolios long-short tail risk (LS_{TR}). We evaluate portfolio returns with seven different factor models:

Model 1 is the simplest, considering only the market risk factor (Sharpe, 1963):

$$R_{LS,t} = \alpha + \beta_{MKT}MKT^{F}{}_{T} + \varepsilon_t. \quad (1)$$

Building on this, Model 2 incorporates the size (SMB) and value (HML) factors, as proposed by (E. Fama & French, 1992):

$$R_{LS,t} = \alpha + \beta_{MKT}MKT^{F}{}_{T} + \beta_{SMB}SMB^{F}{}_{T} + \beta_{MOM}MOM^{F}{}_{T} + \varepsilon_t. \quad (2)$$

Model 3 modifies the factor set, replacing the value factor with the momentum factor:

$$R_{LS,t} = \alpha + \beta_{MKT}MKT^{F}{}_{T} + \beta_{SMB}SMB^{F}{}_{T} + \beta_{MOM}MOM^{F}{}_{T} + \varepsilon_t. \quad (3)$$

Model 4, following (Carhart, 1997), reintroduces the value factor alongside the momentum factor:

$$R_{LS,t} = \alpha + \beta_{MKT}MKT^{F}{}_{T} + \beta_{SMB}SMB^{F}{}_{T} + \beta_{HML}HML^{F}{}_{T} + \beta_{MOM}MOM^{F}{}_{T} + \varepsilon_t. \quad (4)$$

Models 5, 6, and 7 further expand the factor set. Model 5 introduces the betting-against-beta factor:

$$R_{LS,t} = \alpha + \beta_{MKT}MKT^{F}{}_{T} + \beta_{SMB}SMB^{F}{}_{T} + \beta_{HML}HML^{F}{}_{T} + \beta_{MOM}MOM^{F}{}_{T} + \beta_{BAB}BAB^{F}{}_{T} + \varepsilon_t. \quad (5)$$

Model 6 adds the cross-sectional seasonality factor:

$$R_{LS,t} = \alpha + \beta_{MKT}MKT^{F}{}_{T} + \beta_{SMB}SMB^{F}{}_{T} + \beta_{HML}HML^{F}{}_{T} + \beta_{MOM}MOM^{F}{}_{T} + \beta_{BAB}BAB^{F}{}_{T} + \beta_{SEAS}SEAS^{F}{}_{T} + \beta_{IVOL}IVOL^{F}{}_{T} + \varepsilon_t. \quad (6)$$

Finally, Model 7 is the most comprehensive, including idiosyncratic volatility, long-term reversal, and skewness factors:

$$R_{LS,t} = \alpha + \beta_{MKT}MKT^{F}{}_{T} + \beta_{SMB}SMB^{F}{}_{T} + \beta_{HML}HML^{F}{}_{T} + \beta_{MOM}MOM^{F}{}_{T} + \beta_{BAB}BAB^{F}{}_{T} + \beta_{SEAS}SEAS^{F}{}_{T} + \beta_{IVOL}IVOL^{F}{}_{T} + \beta_{REV}REV^{F}{}_{T} + \beta_{SKEW}SKEW^{F}{}_{T} + \varepsilon_t, \quad (7)$$

where $R_{LS,t}$ denotes the LS_{TR} strategy return at month t; β_{MKT}, β_{SMB}, β_{HML}, β_{MOM}, β_{BAB}, β_{SEAS20}, β_{IVOL}, β_{REV} and β_{SKEW24} are factor exposures; α represents the average monthly abnormal return ("alpha"); and ε_t is the error term. Table 1 presents the procedures for calculating the monthly returns on factor portfolios used in models 1-7.

Table 1. Factor Definitions and Calculation Methods.

Factor portfolio	Symbol	Calculation procedure
Market risk factor	MKT^F	The market portfolio excess return, MKT, is the GFD world Index minus the risk-free rate.
Size Factor	$SIZE^F$	First, we rank all the indices on their SIZE values at the end of the previous month. Next, we go long(short) on an equal-weighted portfolio comprising the countries with the highest (lowest) tercile SIZE.
Value Factor	VAL^F	First, we rank all the indices on their D.Y. (Dividend Yield ratio) values at the end of the previous month. Next, we go long(short) on an equal-weighted portfolio comprising the countries with the highest (lowest) tercile VAL.
Momentum Factor	MOM^F	First, we rank all the indices on their MOM (trailing 12-month returns) values at the end of the previous month. Next, we go long(short) on an equal-weighted portfolio comprising the countries with the highest (lowest) tercile MOM.
Long-term reversal factor	REV^F	First, we rank all the indices on their REV (trailing 36-month returns with the most recent 12 months dropped) values at the end of the previous month. Next, we go long (short) on an equal-weighted portfolio comprising the countries with the highest (lowest) tercile REV.
Idiosyncratic risk factor	$IVOL^F$	First, we rank all the indices on their IVOL (idiosyncratic risk from the CAPM based on trailing 12 months. Next, we go long (short) on an equal-weighted portfolio comprising the countries with the highest (lowest) tercile IVOL.
Betting-against-beta factor	BAB^F	To form the portfolio based on the BETA (trailing 12-month) slope coefficient from the CAPM, we follow the approach of Frazzini and Pedersen (2014). Each month, we rank all indices by their BETA at the end of the previous month. Afterward, we calculate the demeaned rank of each index and use it as the index weight in the portfolio. We go long (short) the countries with their BETA above (below) the median. Finally, we leverage (deleverage) the long (short) leg of the long-short portfolio to make the beta equal to unity.
Skewness factor	$SKEW^F$	First, we rank all the indices on their co-skewness (SKEW, trailing 24-month) values at the end of the previous month. Next, we go long (short) on an equal-weighted portfolio comprising the countries with the highest (lowest) tercile SKEW.
Cross-sectional Seasonality factor	$SEAS^F$	First, we rank all the indices on their SEAS (average same-calendar month returns in the past 20 years, as available) values at the end of the previous month. Next, we go long (short) on an equal-weighted portfolio comprising the countries with the highest (lowest) tercile SEAS.

2.4. Cross-Sectional Tests

Beyond the time-series analyses, we also explore the impact of tail risk through cross-sectional regressions, following the methodology proposed by Fama and MacBeth (1973). Within this framework, our objective is to determine the extent to which tail risk measures can predict variations in returns across the cross-section. Accordingly, we execute the subsequent regression for each month within our study period:

$$R_i = \gamma_0 + \gamma_{TR}TR + \sum\nolimits^{n}_{j=1} \gamma_K K^j_i + \varepsilon_t, \quad (8)$$

where R_i denotes the excess return on stock market index i; TR denotes the cross-sectional tail risk measure; K is the set of control variables; γ_0, $\gamma_{TR,}$ and γ_K are estimated monthly regression coefficients; and ε_t represents the random error term. In particular, we are interested in whether the tail risk effects hold after controlling for popular return predictors, including the natural logarithm of the market value (*Log(MV)*), dividend yield ratio (*D.Y.*), trailing 12-month returns (MOM_{12}), trailing 36-month returns with the most recent 12 months dropped (REV_{36}), beta trailing 12-month ($BETA_{12}$), downside beta ($BETA_{down}$), the idiosyncratic volatility from the three-factor Fama & French (1993), trailing 12-month ($IVOL_{12}$), systematic skewness trailing 12-month ($SKEW_{12}$), systematic kurtosis trailing 12-month ($KURT_{12}$), and seasonality as average same-calendar month returns in the past 20 years, as available ($SEAS_{20}$). Table 2 reports summary descriptive statistics for the control variables. In Appendix A in Table A.1, we also report average Pearson correlation coefficients for excess returns, tail risk measures, and control variables.

Table 2. Descriptive statistics of excess returns, tail risk measures, and control variables.

	Obs.	Mean	Std.	Min	Q1	Med.	Q3	Max	Skew.	Kurt.
					Panel A: Excess Returns & Tail risk measures					
Excess Ret	35 454	0.01	0.08	-0.83	-0.03	0.01	0.04	3.33	3.47	109.37
VaR_{60}	32 260	-0.09	0.05	-0.40	-0.11	-0.08	-0.06	0.00	-1.58	4.63
ES_{60}	32 260	-0.14	0.08	-0.71	-0.17	-0.12	-0.08	0.00	-1.96	6.98
Tail β	28 065	1.29	1.68	-14.98	0.42	1.30	2.07	18.72	-0.40	14.55
EDH^{GJR}_{120}	26 244	-0.18	1.59	-6.80	-1.20	-0.27	0.62	13.46	1.16	5.15
$IDIO_{TR}$	28 065	0.62	2.04	-2.35	-0.45	0.17	0.78	10.43	2.01	3.49
					Panel B: Control Variables					
Log(MV)	38 545	2.20	0.39	-2.53	1.99	2.29	2.49	2.84	-1.94	11.80
DY	30 612	3.67	2.33	-0.14	2.21	3.26	4.57	24.16	2.61	12.68
MOM_{12}	33 987	0.12	0.31	-1.60	-0.04	0.11	0.27	3.25	0.66	5.30
REV_{36}	33 124	0.25	0.44	-1.60	0.00	0.23	0.47	6.31	0.82	4.23
$BETA_{12}$	33 969	0.77	0.82	-8.30	0.30	0.77	1.18	16.06	1.69	28.56
$BETA_{down}$	28 065	0.87	0.55	-1.86	0.52	0.95	1.21	3.67	-0.02	0.83
$IVOL_{12}$	33 969	0.05	0.04	0.00	0.03	0.04	0.06	0.75	3.38	21.21
$SKEW_{12}$	33 789	-0.04	0.15	-0.72	-0.12	-0.03	0.06	0.63	-0.43	1.35
$KURT_{12}$	33 789	0.11	0.11	-0.58	0.04	0.11	0.17	0.66	0.18	2.77
$SEAS_{20}$	26 722	0.01	0.02	-0.08	0.00	0.01	0.02	0.19	1.14	7.59

Note. The data is divided into two panels. Panel A provides statistics for excess returns and tail risk measures, including the number of observations, mean, standard deviation, minimum, first quartile (Q1), median (Med.), third quartile (Q3), maximum, skewness, and kurtosis for each measure. The measures include excess returns, VaR_{60}, ES_{60}, Tailβ, EDH^{GJR}_{120}, and $IDIO_{TR}$. Panel B presents similar statistics for all control variables, which include: *Log(MV)*, *D.Y.*, MOM_{12}, REV_{36}, $BETA_{12}$, $BETA_{down}$, $IVOL_{12}$, $SKEW_{12}$, $KURT_{12}$, and $SEAS_{20}$.

4. Results and Discussion

4.1. Baseline Evidence - Portfolio Sorts

Table 3 presents the results of the study for both equal-weighted and value-weighted portfolios based on different tail risk measures. The study results indicate that the T-statistic is nearly zero across all examined cases except Value-at-Risk and Expected Shortfall measures. When considering other factors, all long-short portfolios do not display a statistically significant mean monthly return. This suggests that there is no significant premium associated with tail risk in the distribution of returns. In other words, the market does not reward investors with higher returns for bearing higher tail risk.

For equal-weighted portfolios, the mean returns range from negative value (-0.35% for ES_{60}) to positive (0.15% for EDH^{GJR}_{120}). The volatility of these portfolios is similar (around 4%), with low Sharpe ratios (from -0.25 to 0.13). The alpha values, representing the average monthly abnormal return, vary across different factor models, with some showing positive alpha values and others indicating negative ones.

For value-weighted portfolios, the mean returns range from -0.32% for ES_{60} to 0.14% for EDH^{GJR}_{120}. The volatility of these portfolios is slightly lower than that of equal-weighted portfolios, with the highest being for VaR_{60} and ES_{60} at 4.88%. The Sharpe Ratios are also negative for VaR_{60} and ES_{60}. The alpha values vary across different factor models, similar to the equal-weighted portfolios, but still, absolute alpha values are statistically insignificant and close to zero.

Table 3. Performance of portfolios from one-way sorts on five different tail risk measures.

	Mean	Vol	S.R.	α_1	α_2	α_3	α_4	α_5	α_6	α_7
	Panel A: Equal-weighted portfolios									
VaR_{60}	-0.28	4.98	-0.19	-0.09	0.05	-0.24	-0.06	-0.06	-0.09	-0.14
	(-1.83)			*(-0.6)*	*(0.27)*	*(-1.33)*	*(-0.34)*	*(-0.33)*	*(-0.51)*	*(-0.9)*
ES_{60}	-0.35	4.92	-0.25	-0.19	-0.02	-0.29	-0.09	-0.09	-0.1	-0.14
	(-2.05)			*(-1.08)*	*(-0.09)*	*(-1.56)*	*(-0.54)*	*(-0.53)*	*(-0.57)*	*(-0.95)*
Tail β	0.05	4.24	0.04	-0.02	-0.09	0.01	0.01	0.02	0.03	0.04
	(0.34)			*(-0.11)*	*(-0.54)*	*(0.04)*	*(0.08)*	*(0.1)*	*(0.2)*	*(0.26)*
EDH^{GJR}_{120}	0.15	4.09	0.13	0.21	0.07	0.17	0.09	0.09	0.1	0.09
	(1.05)			*(1.44)*	*(0.45)*	*(1)*	*(0.52)*	*(0.52)*	*(0.6)*	*(0.55)*
$IDIO_{TR}$	0.11	3.79	0.1	0.2	0.1	0.11	0.09	0.09	0.07	0.08
	(0.86)			*(1.49)*	*(0.63)*	*(0.8)*	*(0.62)*	*(0.6)*	*(0.48)*	*(0.52)*
	Panel B: Value-weighted portfolios									
VaR_{60}	-0.25	4.88	-0.18	-0.05	0.08	-0.2	-0.02	-0.02	-0.06	-0.1
	(-1.68)			*(-0.38)*	*(0.43)*	*(-1.12)*	*(-0.11)*	*(-0.1)*	*(-0.33)*	*(-0.69)*
ES_{60}	-0.32	4.88	-0.23	-0.15	0.01	-0.26	-0.06	-0.06	-0.07	-0.12
	(-1.9)			*(-0.88)*	*(0.05)*	*(-1.43)*	*(-0.36)*	*(-0.36)*	*(-0.43)*	*(-0.79)*
Tail β	0.09	4.15	0.08	0.03	-0.07	0.02	0.01	0.02	0.03	0.04
	(0.64)			*(0.25)*	*(-0.42)*	*(0.14)*	*(0.09)*	*(0.1)*	*(0.17)*	*(0.24)*
EDH^{GJR}_{120}	0.14	4.05	0.12	0.19	0.07	0.17	0.08	0.09	0.1	0.09
	(0.99)			*(1.38)*	*(0.41)*	*(1.01)*	*(0.5)*	*(0.51)*	*(0.58)*	*(0.53)*
ITR	0.12	3.7	0.11	0.2	0.09	0.12	0.09	0.09	0.07	0.08
	(0.96)			*(1.56)*	*(0.58)*	*(0.86)*	*(0.65)*	*(0.63)*	*(0.51)*	*(0.56)*

Note. Vol is the standard deviation and S.R. is Sharpe ratio. $\alpha 1$ to $\alpha 7$ indicate the intercepts from factor models (equations 1 to 7), respectively. The numbers in parentheses are Newey-West (1987) adjusted t-statistics. Panels A and B report the results for the equal-weighted and value-weighted portfolios, respectively.

4.2. Cross-Sectional Regressions

The second study employed cross-sectional regression analysis further to investigate the relationship between tail risk and stock market indices returns. Overall, the results of this analysis suggest that while tail risk measures may have some predictive power when considered in isolation, their explanatory power diminishes when other relevant factors are taken into account. This indicates that the tail risk measures do not provide additional explanatory power for differences in stock index returns beyond what other commonly used risk and return factors capture.

When a limited number of variables are included, in some cases, the absolute value of the *T*-statistic exceeds the critical value of 1.96. However, when all control variables are included in the model, the predictive power of tail risk measures for explaining differences in stock index returns diminishes. Specifically, including control variables such as downside beta ($BETA_{down}$) and idiosyncratic volatility ($IVOL_{12}$) contributes to a decrease in the T-statistic for tail risk measures. For instance, when all variables are included, the slope for VaR_{60} becomes positive (0.28) with a t-statistic of 0.73, but for ES_{60}, the slope remains negative (-0.14) with a T-statistic of -1.36.

Table 4. Cross-Sectional Regression Results of Tail Risk (T.R.) Measures and Control Variables.

Variables	VaR_{60} Slope (t-stat)	R^2	ES_{60} Slope (t-stat)	R^2	Tailβ Slope (t-stat)	R^2	EDH^{GJR}_{120} Slope (t-stat)	R^2	ITR Slope (t-stat)	R^2
T.R. measure	-0.05	11.4	-0.04	10.7	0.00	7.5	0.00	8.1	0.00	4.7
	(-2.67)		*(-3.41)*		*(0.04)*		*(0.47)*		*(0.34)*	
T.R. measure & Log.MV	-0.04	19.0	-0.03	17.8	0.00	15.8	0.00	15.0	0.00	12.9
	(-2.31)		*(-2.47)*		*(0.18)*		*(-0.31)*		*(0.65)*	
T.R. measure & DY	-0.02	17.9	-0.03	17.2	0.00	15.5	0.00	15.1	0.00	13.3
	(-1.03)		*(-1.62)*		*(0.18)*		*(-0.14)*		*(0.14)*	
T.R. measure & MOM_{12}	-0.04	21.5	-0.03	21.0	0.00	18.9	0.00	19.1	0.00	17.0
	(-2.02)		*(-2.22)*		*(-0.36)*		*(0.47)*		*(0.12)*	
T.R. measure & REV_{36}	-0.05	19.1	-0.04	18.5	0.00	16.4	0.00	16.3	0.00	14.0
	(-2.83)		*(-3.3)*		*(0.24)*		*(1.33)*		*(-0.13)*	
T.R. measure & $BETA_{12}$	-0.04	20.9	-0.04	20.1	0.00	17.6	0.00	17.2	0.00	15.1
	(-1.94)		*(-3.16)*		*(-0.74)*		*(0.87)*		*(0.28)*	
T.R. measure & $BETA_{down}$	-0.03	19.5	-0.03	19.0	0.00	16.0	0.00	16.7	0.00	13.5
	(-1.2)		*(-2.21)*		*(-0.26)*		*(0.16)*		*(0.2)*	
T.R. measure & $IVOL_{12}$	-0.02	20.0	-0.03	19.4	0.00	18.5	0.00	17.6	0.00	16.2
	(-1.23)		*(-1.97)*		*(-0.13)*		*(0.66)*		*(-0.24)*	
T.R. measure & $SKEW_{12}$	-0.05	17.0	-0.04	16.3	0.00	14.0	0.00	14.1	0.00	11.4
	(-2.64)		*(-3.34)*		*(0)*		*(0.13)*		*(0.41)*	
T.R. measure & $KURT_{12}$	-0.06	17.7	-0.04	17.0	0.00	14.0	0.00	14.2	0.00	11.5
	(-2.79)		*(-3.38)*		*(-0.09)*		*(0.19)*		*(-0.09)*	
T.R. measure & $SEAS_{20}$	-0.03	20.3	-0.02	19.1	0.00	15.7	0.00	15.4	0.00	13.2
	(-1.42)		*(-1.69)*		*(-0.08)*		*(-0.26)*		*(1.35)*	
All variables	0.28	69.6	-0.14	69.7	0.00	69.4	0.00	69.1	0.00	68.6
	(0.73)		*(-1.36)*		*(-0.61)*		*(0.33)*		*(-0.61)*	

Note. The tail risk measures include VaR_{60}, ES_{60}, Tailβ, EDH^{GJR}_{120}, and $IDIO_{TR}$. For each tail risk measure, the table provides the slope and t-statistics of the regression line, as well as the R-squared value. The control variables include *Log(MV)*, *DY*, MOM_{12}, REV_{36}, $BETA_{12}$, $BETA_{down}$, $IVOL_{12}$, $SKEW_{12}$, $KURT_{12}$, and $SEAS_{20}$.

4.2. Robustness Checks

Finally, we corroborate our results with a battery of additional robustness checks. The first analysis was conducted by dividing the sample into two equal-length sub-periods. The long-short portfolios were also split into equal-weighted and value-weighted portfolios for this analysis. The t-statistics were relatively close to zero except for the TailBeta measure in the first half. This suggests that a higher level of tail risk measure is not linked with an additional premium achieved from investments in stock indices, for which this risk is higher. What is also interesting is that alphas were more often positive in the first subset than in the second half.

This robustness check analysis further confirms the original proposition from the main study, reinforcing the conclusion that tail risk measures do not provide additional explanatory power for differences in stock index returns beyond what is captured by other commonly used risk and return factors.

Table 5. Robustness check analysis: performance of portfolios sorted on tail risk measures

Variable	α_1	α_2	α_3	α_4	α_5	α_6	α_7
	Panel A: Equal-weighted portfolios						
	The first half of the sample period						
VaR_{60}	0.25	0.35	0.02	0.05	0.03	-0.26	-0.08
	(1.42)	*(1.19)*	*(0.06)*	*(0.17)*	*(0.1)*	*(-0.93)*	*(-0.31)*
ES_{60}	0.06	0.06	-0.13	-0.12	-0.12	-0.4	-0.23
	(0.22)	*(0.21)*	*(-0.46)*	*(-0.41)*	*(-0.41)*	*(-1.32)*	*(-0.8)*
Tail β	0.23	0.06	0.41	0.4	0.45	0.67	0.59
	(0.92)	*(0.17)*	*(1.17)*	*(1.22)*	*(1.33)*	*(2.41)*	*(2.32)*
EDH^{GJR}_{120}	0.51	0.25	0.37	0.29	0.26	0.32	0.31
	(2.14)	*(0.88)*	*(1.14)*	*(0.97)*	*(0.9)*	*(1.18)*	*(1.23)*
$IDIO_{TR}$	0.39	0.12	0.14	0.07	0.01	-0.04	-0.04
	(1.91)	*(0.46)*	*(0.51)*	*(0.24)*	*(0.04)*	*(-0.15)*	*(-0.16)*
	The second half of the sample period						
VaR_{60}	-0.38	-0.07	-0.35	-0.13	-0.13	-0.11	-0.21
	(-1.71)	*(-0.29)*	*(-1.6)*	*(-0.64)*	*(-0.64)*	*(-0.52)*	*(-1.19)*
ES_{60}	-0.4	-0.06	-0.36	-0.13	-0.13	-0.09	-0.18
	(-1.69)	*(-0.27)*	*(-1.58)*	*(-0.61)*	*(-0.61)*	*(-0.43)*	*(-1.05)*
Tail β	-0.14	-0.12	-0.08	-0.07	-0.07	-0.08	-0.06
	(-0.78)	*(-0.63)*	*(-0.4)*	*(-0.36)*	*(-0.36)*	*(-0.42)*	*(-0.3)*
EDH^{GJR}_{120}	0.04	-0.02	0.1	0.01	0.01	0.01	-0.02
	(0.22)	*(-0.09)*	*(0.51)*	*(0.04)*	*(0.04)*	*(0.04)*	*(-0.09)*
$IDIO_{TR}$	0.1	0.07	0.09	0.07	0.07	0.07	0.09
	(0.58)	*(0.38)*	*(0.53)*	*(0.41)*	*(0.42)*	*(0.39)*	*(0.53)*
	Panel B: Value-weighted portfolios						
	The first half of the sample period						
VaR_{60}	0.31	0.45	0.14	0.14	0.12	-0.24	-0.07
	(1.76)	*(1.56)*	*(0.46)*	*(0.48)*	*(0.39)*	*(-0.92)*	*(-0.3)*
ES_{60}	0.12	0.1	-0.08	-0.09	-0.11	-0.44	-0.26
	(0.49)	*(0.37)*	*(-0.28)*	*(-0.32)*	*(-0.35)*	*(-1.46)*	*(-0.89)*
Tail β	0.25	0.14	0.46	0.48	0.52	0.71	0.65
	(1.06)	*(0.45)*	*(1.37)*	*(1.5)*	*(1.58)*	*(2.64)*	*(2.52)*
EDH^{GJR}_{120}	0.5	0.19	0.33	0.23	0.21	0.26	0.24
	(2.1)	*(0.7)*	*(1.09)*	*(0.83)*	*(0.75)*	*(1.01)*	*(0.96)*
$IDIO_{TR}$	0.41	0.08	0.18	0.09	0.03	-0.04	-0.06
	(2.03)	*(0.31)*	*(0.67)*	*(0.32)*	*(0.12)*	*(-0.13)*	*(-0.2)*
	The second half of the sample period						
VaR_{60}	-0.37	-0.07	-0.33	-0.12	-0.12	-0.09	-0.18
	(-1.67)	*(-0.31)*	*(-1.55)*	*(-0.58)*	*(-0.59)*	*(-0.45)*	*(-1.07)*
ES_{60}	-0.38	-0.05	-0.34	-0.11	-0.11	-0.07	-0.15
	(-1.61)	*(-0.24)*	*(-1.52)*	*(-0.52)*	*(-0.52)*	*(-0.33)*	*(-0.9)*
Tail β	-0.07	-0.11	-0.07	-0.08	-0.08	-0.09	-0.07
	(-0.42)	*(-0.59)*	*(-0.36)*	*(-0.43)*	*(-0.43)*	*(-0.5)*	*(-0.39)*
EDH^{GJR}_{120}	0.03	-0.01	0.11	0.02	0.02	0.02	-0.01
	(0.2)	*(-0.07)*	*(0.57)*	*(0.09)*	*(0.09)*	*(0.1)*	*(-0.04)*
$IDIO_{TR}$	0.11	0.07	0.09	0.07	0.07	0.07	0.09
	(0.62)	*(0.39)*	*(0.56)*	*(0.43)*	*(0.43)*	*(0.4)*	*(0.54)*

Note. This table presents the results of the robustness check analysis, where the sample was divided into two equal-length sub-periods. The analysis was conducted on both equal-weighted and value-weighted portfolios. The table reports the alpha values ($\alpha 1$ to $\alpha 7$) from factor models for five different tail risk measures. The numbers in parentheses are Newey-West (1987) adjusted t-statistics. Panels A and B report the results for the equal-weighted and value-weighted portfolios, respectively, for each half of the sample period. This analysis further investigates the relationship between tail risk measures and the performance of stock index portfolios.

The robustness check analysis was further extended by shortening the sample period and conducting the study in three variants. This was done to ensure the comparability of the results with those of other researchers and to further validate the initial analysis findings. In conclusion, the robustness check analysis, conducted in three distinct variants, consistently affirmed our initial proposition. When control variables were integrated into the regression model, it did not result in an exceedance of the significance level. This indicates that a higher level of tail risk measure does not translate into an additional premium achieved from investments in stock indices, for which this risk is higher. This finding is consistent across different periods and portfolio weighting methods, further strengthening the validity of our initial analysis. Table 6 presents the results from the period starting from, following, the starting date of Atilgan et al. (2020).

Table 6. Performance of portfolios from one-way sorts on five different tail risk measures for the subsample includes data from January 1961. This period selection is in line with the sample period used in the study by Atilgan et al. (2020)., thus allowing for a comparison of results.

Tail risk	Mean	α_1	α_2	α_3	α_4	α_5	α_6	α_7
	Panel A: Equal-weighted portfolios							
VaR_{60}	-0.39	-0.25	-0.02	-0.32	-0.13	-0.13	-0.1	-0.16
	(-1.95)	*(-1.31)*	*(-0.1)*	*(-1.69)*	*(-0.71)*	*(-0.71)*	*(-0.57)*	*(-1.03)*
ES_{60}	-0.45	-0.33	-0.04	-0.34	-0.13	-0.13	-0.09	-0.14
	(-2.18)	*(-1.65)*	*(-0.21)*	*(-1.71)*	*(-0.72)*	*(-0.71)*	*(-0.49)*	*(-0.89)*
Tail β	-0.09	-0.18	-0.11	-0.02	-0.01	-0.01	-0.01	0
	(-0.52)	*(-1.1)*	*(-0.62)*	*(-0.13)*	*(-0.05)*	*(-0.05)*	*(-0.08)*	*(-0.01)*
EDH^{GJR}_{120}	0.06	0.11	0.08	0.2	0.11	0.11	0.1	0.09
	(0.4)	*(0.7)*	*(0.47)*	*(1.14)*	*(0.61)*	*(0.61)*	*(0.58)*	*(0.52)*
$IDIO_{TR}$	0.09	0.13	0.06	0.08	0.06	0.06	0.05	0.06
	(0.6)	*(0.87)*	*(0.38)*	*(0.55)*	*(0.38)*	*(0.39)*	*(0.35)*	*(0.4)*
	Panel B: Value-weighted portfolios							
VaR_{60}	-0.37	-0.23	-0.01	-0.3	-0.11	-0.11	-0.08	-0.13
	(-1.87)	*(-1.22)*	*(-0.03)*	*(-1.61)*	*(-0.6)*	*(-0.61)*	*(-0.45)*	*(-0.88)*
ES_{60}	-0.43	-0.31	-0.02	-0.33	-0.11	-0.11	-0.07	-0.12
	(-2.06)	*(-1.53)*	*(-0.12)*	*(-1.67)*	*(-0.63)*	*(-0.62)*	*(-0.38)*	*(-0.77)*
Tail β	-0.02	-0.1	-0.09	-0.01	-0.01	-0.01	-0.02	-0.01
	(-0.11)	*(-0.64)*	*(-0.51)*	*(-0.05)*	*(-0.06)*	*(-0.07)*	*(-0.11)*	*(-0.04)*
EDH^{GJR}_{120}	0.05	0.09	0.07	0.2	0.1	0.1	0.1	0.09
	(0.33)	*(0.62)*	*(0.44)*	*(1.16)*	*(0.6)*	*(0.61)*	*(0.57)*	*(0.5)*
$IDIO_{TR}$	0.09	0.12	0.05	0.08	0.05	0.05	0.05	0.06
	(0.59)	*(0.81)*	*(0.31)*	*(0.54)*	*(0.36)*	*(0.36)*	*(0.32)*	*(0.38)*

Note. $\alpha 1$ to $\alpha 7$ indicate the intercepts from factor models (equations 1 to 7), respectively. The numbers in parentheses are Newey-West (1987) adjusted t-statistics. Panels A and B report the results for the equal-weighted and value-weighted portfolios, respectively.

Table 7 presents the results from the period starting from 1968 to the end, following the starting dates of Van Oordt & Zhou (2016) and Harris et al. (2019). Similar to Table A, the mean alpha values for both equal-weighted and value-weighted portfolios were close to zero, further confirming the initial proposition.

Table 8 presents the results from the period starting from 1980 to the end. The results from this period show a slight variation with more positive mean alpha values, but the overall trend remains consistent with the previous periods.

Appendix A shows a robustness check for cross-sectional regression analysis. We expanded the Value at Risk (VaR) estimation window and Expected Shortfall (ES) risk measures. The findings from this analysis align with our baseline analysis, reinforcing its validity. The results suggest that while tail risk measures may exhibit some predictive capacity when evaluated independently, their explanatory power tends to wane when other pertinent factors are considered. This implies that the tail risk measures do not contribute additional explanatory power to the variations in stock index returns beyond what is captured by other commonly used risk and return factors.

Table 7. Performance of portfolios from one-way sorts on five different tail risk measures for the subsample includes data from January 1968. This period selection is in line with the sample period used in the studies by Harris et al. (2019) and Van Oordt & Zhou (2016), thus allowing for a comparison of results.

Tail risk	Mean	α_1	α_2	α_3	α_4	α_5	α_6	α_7
	Panel A: Equal-weighted portfolios							
VaR_{60}	-0.45	-0.31	-0.01	-0.31	-0.11	-0.11	-0.09	-0.15
	(-2.1)	*(-1.5)*	*(-0.05)*	*(-1.56)*	*(-0.59)*	*(-0.59)*	*(-0.49)*	*(-0.92)*
ES_{60}	-0.54	-0.41	-0.07	-0.37	-0.16	-0.16	-0.12	-0.17
	(-2.41)	*(-1.89)*	*(-0.34)*	*(-1.78)*	*(-0.8)*	*(-0.8)*	*(-0.61)*	*(-1.04)*
Tail β	-0.07	-0.15	-0.11	-0.06	-0.03	-0.03	-0.04	-0.03
	(-0.39)	*(-0.91)*	*(-0.59)*	*(-0.3)*	*(-0.18)*	*(-0.18)*	*(-0.2)*	*(-0.14)*
EDH^{GJR}_{120}	0.12	0.17	0.1	0.21	0.11	0.11	0.1	0.09
	(0.74)	*(1.05)*	*(0.55)*	*(1.12)*	*(0.59)*	*(0.59)*	*(0.57)*	*(0.48)*
$IDIO_{TR}$	0.08	0.12	0.08	0.1	0.08	0.08	0.08	0.09
	(0.48)	*(0.74)*	*(0.46)*	*(0.65)*	*(0.49)*	*(0.5)*	*(0.46)*	*(0.53)*
	Panel B: Value-weighted portfolios							
VaR_{60}	-0.43	-0.29	0	-0.29	-0.1	-0.1	-0.08	-0.12
	(-2.01)	*(-1.41)*	*(-0.02)*	*(-1.5)*	*(-0.51)*	*(-0.52)*	*(-0.4)*	*(-0.77)*
ES_{60}	-0.5	-0.38	-0.06	-0.36	-0.14	-0.14	-0.1	-0.15
	(-2.27)	*(-1.76)*	*(-0.28)*	*(-1.75)*	*(-0.74)*	*(-0.74)*	*(-0.55)*	*(-0.92)*
Tail β	0	-0.07	-0.08	-0.03	-0.03	-0.03	-0.03	-0.02
	(0.02)	*(-0.44)*	*(-0.47)*	*(-0.17)*	*(-0.15)*	*(-0.15)*	*(-0.19)*	*(-0.14)*
EDH^{GJR}_{120}	0.11	0.16	0.09	0.21	0.11	0.11	0.11	0.09
	(0.67)	*(0.97)*	*(0.55)*	*(1.16)*	*(0.61)*	*(0.61)*	*(0.6)*	*(0.51)*
$IDIO_{TR}$	0.08	0.11	0.07	0.1	0.07	0.07	0.07	0.08
	(0.47)	*(0.68)*	*(0.39)*	*(0.63)*	*(0.46)*	*(0.46)*	*(0.42)*	*(0.49)*

Note. $\alpha 1$ to $\alpha 7$ indicate the intercepts from factor models (equations 1 to 7), respectively. The numbers in parentheses are Newey-West (1987) adjusted t-statistics. Panels A and B report the results for the equal-weighted and value-weighted portfolios, respectively.

5. Conclusions

This study has provided a comprehensive analysis of the predictive power of tail risk measures for stock index returns, taking into account a variety of control variables. Our findings suggest that while tail risk measures may exhibit some predictive power when considered in isolation, their explanatory power diminishes when other relevant factors are considered. This indicates that tail risk measures do not provide additional explanatory power for differences in stock index returns beyond what other commonly used risk and return factors capture.

The robustness of our results was confirmed through sensitivity analyses, which involved adjusting the window for estimating VaR and ES risk measures and conducting cross-sectional regression analyses. These robustness checks further reinforced our main findings, demonstrating the consistency of the results across different model specifications and periods.

However, it is important to note that our research has limitations. While our research focused on stock index returns, the findings may have broader implications for the pricing of other financial assets and the management of financial risks. Therefore, future research could also investigate the applicability of our findings to other financial markets and investment strategies.

The findings of this research carry practical implications for investors and financial risk managers. When other relevant factors are considered, the diminished predictive power of tail risk measures suggests that a holistic approach, incorporating a broad range of risk and return factors, should be adopted in investment strategies and financial risk management. While tail risk measures may not provide additional explanatory power for differences in stock index returns, they remain integral to comprehensive risk management strategies.

Table 8. Performance of portfolios from one-way sorts on five different tail risk measures for the subsample includes data from January 1980. This period selection is in line with the sample period used in the studies by Long, Zhu, et al. (2019) and Ang et al. (2009), thus allowing for a comparison of results.

	Mean	α_1	α_2	α_3	α_4	α_5	α_6	α_7
				Panel A: Equal-weighted portfolios				
VaR_{60}	-0.39	-0.24	0.11	-0.2	0.08	0.08	0.12	0.04
	(-1.61)	*(-1)*	*(0.5)*	*(-0.85)*	*(0.39)*	*(0.39)*	*(0.61)*	*(0.23)*
ES_{60}	-0.42	-0.27	0.14	-0.22	0.07	0.07	0.12	0.04
	(-1.59)	*(-1.02)*	*(0.6)*	*(-0.89)*	*(0.32)*	*(0.32)*	*(0.58)*	*(0.26)*
Tail β	-0.03	-0.14	-0.13	-0.12	-0.09	-0.09	-0.13	-0.11
	(-0.15)	*(-0.74)*	*(-0.67)*	*(-0.6)*	*(-0.47)*	*(-0.47)*	*(-0.67)*	*(-0.58)*
EDH^{GJR}_{120}	0.08	0.11	0.01	0.14	0.06	0.06	0.05	0.04
	(0.5)	*(0.61)*	*(0.08)*	*(0.68)*	*(0.29)*	*(0.29)*	*(0.26)*	*(0.22)*
$IDIO_{TR}$	0.01	0.06	0.02	0.03	0.01	0.01	0.01	0.02
	(0.05)	*(0.31)*	*(0.1)*	*(0.16)*	*(0.08)*	*(0.08)*	*(0.05)*	*(0.13)*
				Panel B: Value-weighted portfolios				
VaR_{60}	-0.38	-0.24	0.09	-0.2	0.07	0.07	0.12	0.05
	(-1.59)	*(-1)*	*(0.43)*	*(-0.87)*	*(0.37)*	*(0.38)*	*(0.62)*	*(0.35)*
ES_{60}	-0.42	-0.26	0.13	-0.22	0.07	0.07	0.13	0.06
	(-1.56)	*(-1.01)*	*(0.56)*	*(-0.91)*	*(0.35)*	*(0.34)*	*(0.61)*	*(0.4)*
Tail β	0.02	-0.08	-0.13	-0.11	-0.11	-0.11	-0.15	-0.13
	(0.11)	*(-0.42)*	*(-0.67)*	*(-0.58)*	*(-0.57)*	*(-0.57)*	*(-0.79)*	*(-0.73)*
EDH^{GJR}_{120}	0.09	0.11	0.03	0.15	0.07	0.07	0.06	0.05
	(0.56)	*(0.66)*	*(0.15)*	*(0.73)*	*(0.34)*	*(0.34)*	*(0.32)*	*(0.27)*
$IDIO_{TR}$	0.01	0.05	0	0.02	0	0	-0.01	0
	(0.04)	*(0.25)*	*(0)*	*(0.09)*	*(-0.02)*	*(-0.02)*	*(-0.05)*	*(0.01)*

Note. α1 to α7 indicate the intercepts from factor models (equations 1 to 7), respectively. The numbers in parentheses are Newey-West (1987) adjusted t-statistics. Panels A and B report the results for the equal-weighted and value-weighted portfolios, respectively.

Supplementary Materials: Appendix is available from the author.

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