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Stock Return Jumps and Tail Risk Assessment: The Case of European Non-Euro Banking Sectors

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Abstract

This study investigates the linkages between stock return jumps, volatilities, and tail risks in European non-euro banking sectors over the period 2005─2020. As a result, our examinations derive the following significant findings. First, for European non-euro banking sectors, in extending EGARCH models, taking bidirectional stock return jumps into consideration is always effective. Second, for European non-euro banking sector stocks, in extending EGARCH models, incorporating skewed and fat-tailed or fat-tailed densities is also effectual. In addition, our additional analyses further find that when taking bidirectional return jumps into account, the volatility estimates from our extended EGARCH models more precisely capture the tail risks in European non-euro banking sector stocks. This signifies that if we ignore bidirectional stock return jumps, we will undervalue the levels of tail risks when stock prices of international banking sectors plunge.

Keywords: European non-euro banking sector, risk assessment, stock return jump, tail risk, EGARCH model, probit model

1. Introduction

The banking sector is the core for financial industries and in Europe, the UK banking sector is particularly important as the UK financial markets play a central role in Europe. Further, the Swiss banking sector is also significant in Europe as the businesses and transactions of Swiss banks are generally precise. We here note that the UK and Switzerland are both non-euro European countries. Considering this categorization by noting the G10, Sweden is also a G10 non-euro European country like the UK and Switzerland, and thus, it is reasonable for us to include the Swedish banking sector in our analyses. Because of these reasons and backgrounds, this study focuses on the European non-euro banking sectors of the UK, Sweden, and Switzerland.

As stock return volatility jumps and stock market plunges in the US at the time of the recent COVID-19 crisis clearly showed, bidirectional stock return jumps and tail risks are strongly connected. Indeed, there exist previous studies on stock return breaks (e.g., Adesina, 2017; Yin, 2019) and on tail risks (e.g., Duffie and Pan, 1997; Tsuji, 2016); however, to our best knowledge, there is little research that investigated the empirical connections between bidirectional return jumps, volatilities, and tail risks in European non-euro banking sectors all together. Given these, our research question of this study is, how are stock return jumps, stock return volatilities, and tail risks in European non-euro banking sectors connected?

To answer this research question, our current study investigates the explanatory power of tail risks for the European non-euro banking sector stocks of the UK, Sweden, and Switzerland. As a result of our rigorous quantitative analysis, this study derives the following significant new findings. First, for the cases we analyzed in this study, in extending exponential generalized autoregressive conditional heteroscedasticity (EGARCH) models (Nelson, 1991), taking bidirectional stock return jumps into consideration is always effective for estimating volatilities. Second, for the cases we examined in this study, in extending EGARCH models, incorporating not only bidirectional return jumps but also the skew-*t* or Student-*t* density simultaneously is particularly meaningful for estimating volatilities more accurately.

Moreover, our additional analysis using probit models further clarifies that when taking bidirectional return jumps into account, the volatility estimates from our extended EGARCH models more precisely capture the equity tail risks of the three European non-euro banking sectors. This clearly shows that if we ignore bidirectional return jumps in volatility estimations, we will undervalue the levels of tail risks when stock prices of international banking sectors plunge.

As regards the article organization, after this introduction, Section 2 reviews related past literature, Section 3 describes our data, and Section 4 explains our models and investigating methodology. Afterwards, Section 5 provides our results, and finally, Section 6 provides our conclusions.

2. Literature Review

This section briefly reviews extant research related to our current study. First, Tsuji (2016) quantitatively inspected and showed that, in forecasting the US stock market tail risks, US volatility index (VIX) did not outperform the S&P 500 volatility forecasts from econometric models, but this study did not take stock return jumps into consideration. Elsewhere, Ewing and Malik (2016) empirically analyzed the volatility spillover effects between oil and equity markets by taking return breaks into account; however, they have little perspective of tail risk assessment.

Further, Tsuji (2017) quantitatively examined and evidenced that the previous day’s US S&P 500 VIX changes have predictive power for the tail risks of the TOPIX in Japan; however, the analyses of this study did not include stock return jumps. Moreover, focusing on the period that includes the Brexit vote, Adesina (2017) empirically explored the effect of return breaks on the volatility persistence of the FTSE 100 stock price index returns, but this study either has few viewpoints of tail risk management. In addition, focusing on the European markets, a quantitative study by Tsuji (2018a) mainly revealed that the increases of the UK VIX have predictive power for the tail risks in other European stock markets of France, Italy, Spain, and Portugal; however, this study did not consider the effects of stock return jumps.

Afterwards, Tsuji (2018b) quantitatively examined the spillover effects between international oil equities; however, in this study, the effects of stock return jumps were only partly considered. Moreover, Yin (2019) empirically explored the US equity premium also by taking the breaks in stock returns into consideration; however, this study has few perspectives of tail risk assessment. More recently, Tsuji (2020) also quantitatively inspected the spillover effects between international banking sector stocks, but in this study, the effects of stock return jumps were again only partly analyzed. More recently, Ma et al. (2019) proposed new jump indexes that are connected with the jump information on the G7 equity markets to forecast the US stock market volatility. Zhang et al. (2022) investigated the contagion effect of jump risks across Asian equity markets during the COVID-19 crisis, but these two studies did not analyze tail risks.

As the above literature review clearly indicates, we understand that there is little research that investigated bidirectional return jumps from the perspective of risk assessment and management, although stock return jumps and tail risks are tightly connected as the past Lehman crisis and the recent COVID-19 crisis demonstrated. Therefore, in this study, using European non-euro banking sector stock data and focusing on their tail risks, we quantitatively examine whether considering bidirectional stock return jumps is effective in capturing the tail risks in the three banking sectors of the UK, Sweden, and Switzerland.

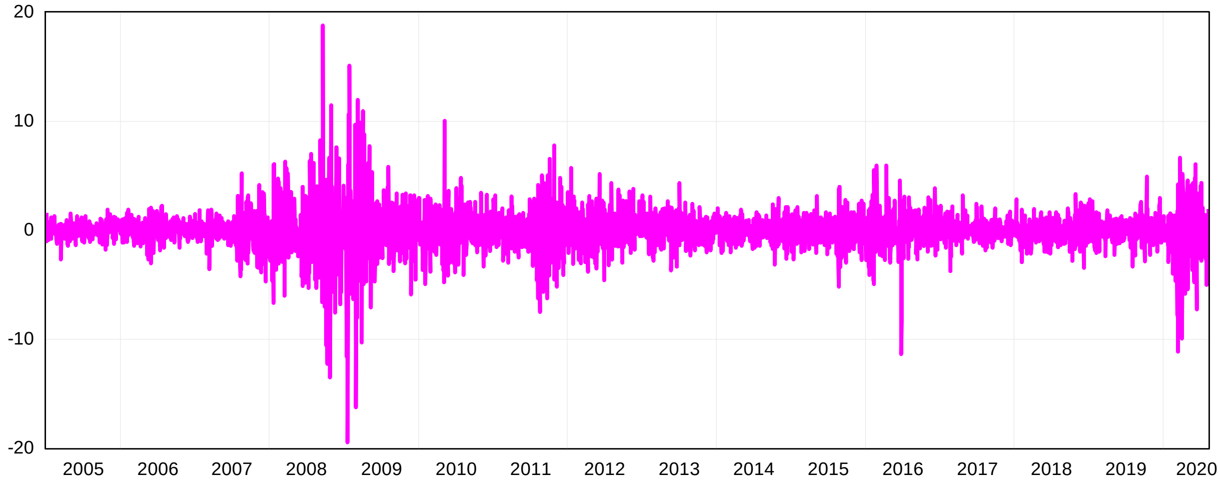
3. Data

This section explains our data. In this study, we examine the daily returns of the stock price indices of the three European non-euro banking sectors. More concretely, this study uses the daily returns of the banking sector stock price indices of the UK, Sweden, and Switzerland. These index data are in British pound sterling for the UK, Swedish krona for Sweden, and Swiss franc for Switzerland, respectively. Using these price data, we compute the daily log difference percentage returns for our analyses.

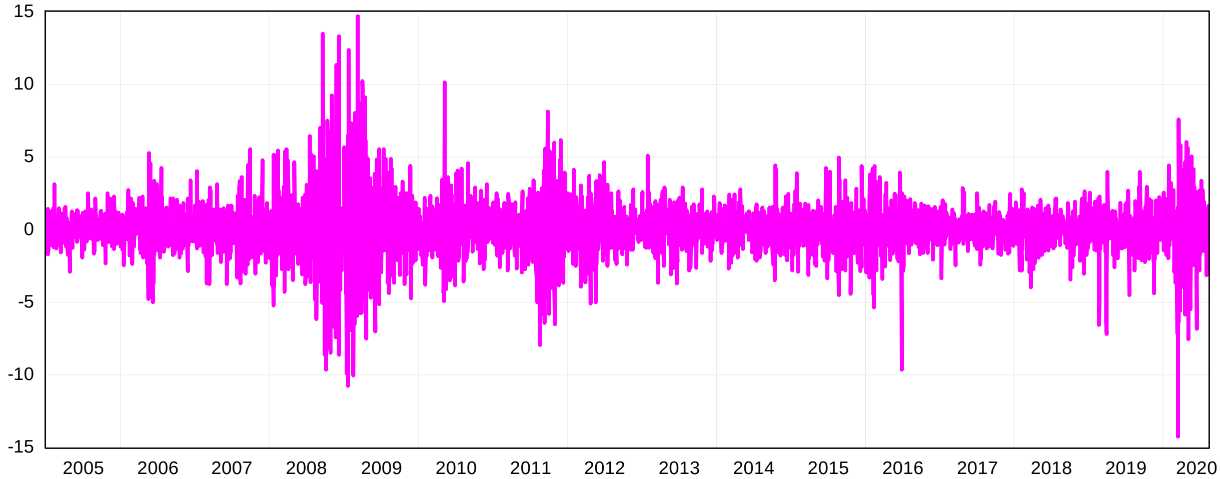
Figure 1 displays the dynamic evolution of the banking sector stock returns of these three countries. We note that in our sample period, we identified the number of return jumps for the UK, Sweden, and Switzerland, and they are 15, 13, and 11, respectively. As in Ewing and Malik (2016) and Tsuji (2020), the return jumps were identified by the iterated cumulative sums of squares (ICSS) algorithm also in this study. The sample period we analyze in this paper is from January 4, 2005 to August 10, 2020.

Table 1 exhibits the descriptive statistics for the three banking sector stock returns. As in Table 1, these return series record the larger values of kurtosis for the UK (17.341), Sweden (11.247), and Switzerland (13.363). We note that these values clearly exceed the kurtosis value of normal distributions, and this means that all the three European non-euro banking sector stock returns exhibit fat tails. Table 1 also shows that by the Jarque–Bera statistics, the normality of all the three banking sector stock returns is clearly rejected. That is, we understand that in our investigations, we should consider fat-tailed distributions of the three banking stock return series of the UK, Sweden and Switzerland.

Panel A. UK



Panel B. Sweden



Panel C. Switzerland

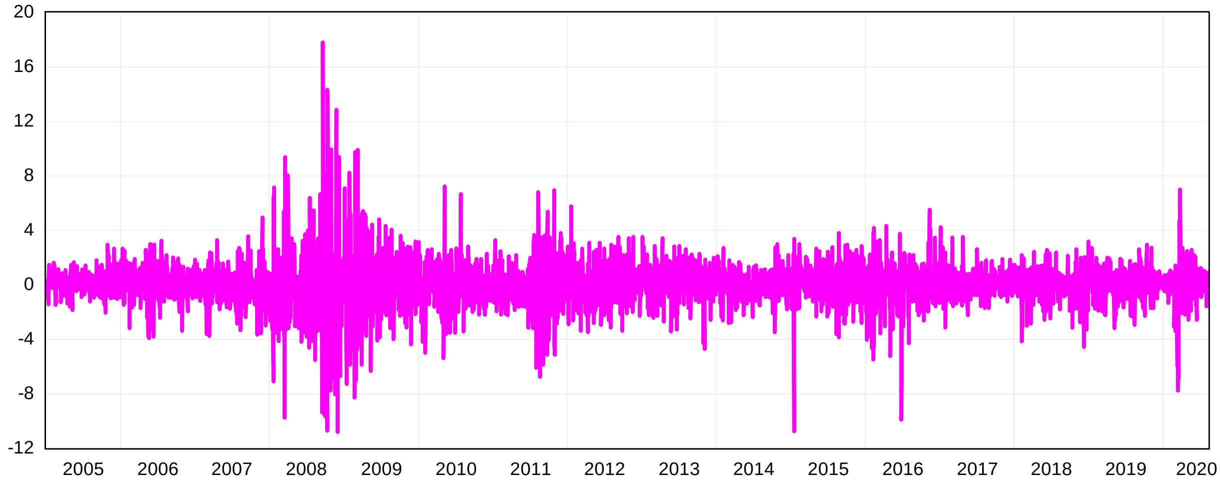


Figure 1. Daily log stock return evolution in European non-euro banking sectors

Table 1. Descriptive statistics of daily log returns in European non-euro banking sectors

	UK	Sweden	Switzerland
Mean	−0.039	0.008	−0.019
SD	1.856	1.825	1.737
Skewness	−0.262	0.163	0.163
Kurtosis	17.341	11.247	13.363
JB	34925.30	11552.42	18228.95
p-value	0.000	0.000	0.000
ADF	−62.186	−48.005	−38.916
p-value	0.000	0.000	0.000

Note. Statistics are for daily log percentage returns. SD means the standard deviation value, JB indicates the Jarque–Bera statistic, and ADF means the augmented Dickey–Fuller test statistic, respectively.

4. Models and Methodology

4.1 Models

This section explains our models and methodology. To consider the effects of bidirectional return jumps, this study uses standard and extended EGARCH models by considering return jumps and skewed and fat-tailed densities. First, we specify the standard EGARCH model without considering return jumps as follows:

$$dlr_t = \kappa_0 + \sum_{i=1}^{q} \kappa_i dlr_{t-i} + \eta_t, \tag{1}$$

$$\ln(h_t) = \mu + \phi \ln(h_{t-1}) + \chi \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \psi \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}}. \tag{2}$$

In Equation (1), dlr_t indicates one of the three countries' banking sector stock returns at time t, and dlr_{t-i} indicates the i-th lag of one of the three countries' banking sector stock returns. Further, η_t indicates the error term, for which we employ and examine not only common normal distribution errors as in many previous studies but also Student-t and skew-t distribution errors. Moreover, h_t (h_{t-1}) in Equation (2) indicates one of the three countries' banking sector stock returns' variances at time t ($t-1$).

We next specify the extended EGARCH model, which takes bidirectional return jumps into account as follows:

$$dlr_t = \kappa_0 + \sum_{i=1}^{q} \kappa_i dlr_{t-i} + \eta_t,$$

$$\ln(h_t) = \mu + \phi \ln(h_{t-1}) + \chi \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \psi \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}} + \sum_{i=1}^{n} \kappa_i JD_{i,t}. \tag{3}$$

The mean equation of this extended EGARCH model is the same as Equation (1). The presence of the final term in Equation (3) is the only difference between Equations (2) and (3), where $JD_{i,t}$ indicates the dummy variables that capture the bidirectional return jumps. More concretely, $JD_{i,t}$ equals one from the i-th return jump point onwards and zero elsewhere. In addition, n means the number of the return jumps that the ICSS algorithm identified. As regards the variance equation of our extended EGARCH model in Equation (3), the other notations are the same as in Equation (2). Moreover, in Equations (2) and (3), the ARCH effect is captured by the parameter ψ, the GARCH effect is captured by the parameter ϕ, and the asymmetry of return shock effects on volatilities is captured by the parameter χ.

4.2 Tail Risk Assessment Methodology

After estimating volatilities by the above models, as in Tsuji (2016), using probit models and VaRs, we test the tail risk explanatory power of our estimated volatilities as follows:

$$\Delta p_t = m + \beta z_t + \varepsilon_t, \tag{4}$$

$$y_t = \begin{cases} 1 & \text{if } \Delta p_t \le (100 - p)\%\text{VaR} \\ 0 & \text{if } \Delta p_t > (100 - p)\%\text{VaR} \end{cases},$$

where Δp_t indicates each country's banking sector stock price change and $(100-p)$ takes a value of 95, 98, or 99. In addition, z_t indicates each of our volatility estimates, that is, the estimated volatility from the EGARCH model with normal distribution errors, that from the EGARCH model with Student-*t* or skew-*t* distribution errors, or that from the EGARCH model with Student-*t* or skew-*t* distribution errors and considering bidirectional return jumps. Therefore, in Equation (4), a positive coefficient of β indicates the tail risk explanatory power of the estimated volatilities.

Table 2. Estimation results for the EGARCH models with or without considering bidirectional return jumps

Panel A. EGARCH with normal distribution errors			
	UK	Sweden	Switzerland
μ	−0.117**	−0.094**	−0.114**
p-value	0.000	0.000	0.000
ψ	0.163**	0.140**	0.168**
p-value	0.000	0.000	0.000
ϕ	0.991**	0.985**	0.981**
p-value	0.000	0.000	0.000
χ	−0.070**	−0.080**	−0.100**
p-value	0.000	0.000	0.000
LL	−6970.678	−7257.829	−7008.466
Panel B. EGARCH with Student-t or skew-t errors			
	UK §	Sweden §§	Switzerland §
μ	−0.110**	−0.099**	−0.104**
p-value	0.000	0.000	0.000
ψ	0.154**	0.146**	0.149**
p-value	0.000	0.000	0.000
ϕ	0.990**	0.987**	0.985**
p-value	0.000	0.000	0.000
χ	−0.079**	−0.084**	−0.089**
p-value	0.000	0.000	0.000
DOF	6.492**	5.891**	6.268**
p-value	0.000	0.000	0.000
LS		−0.044*	
p-value		0.032	
LL	−6885.438	−7146.667	−6912.365
Panel C. EGARCH with Student-t or skew-t errors and considering bidirectional return jumps			
	UK §	Sweden §§	Switzerland §
μ	−0.224**	−0.115**	−0.126**
p-value	0.000	0.000	0.000
ψ	0.135**	0.141**	0.144**
p-value	0.000	0.000	0.000

ϕ	0.836**	0.853**	0.916**
p-value	0.000	0.000	0.000
χ	−0.110**	−0.148**	−0.129**
p-value	0.000	0.000	0.000
κ_1	0.153**	0.204**	0.030
p-value	0.004	0.002	0.109
κ_2	−0.124*	−0.122*	0.049
p-value	0.017	0.032	0.108
κ_3	0.355**	0.193**	0.103**
p-value	0.000	0.000	0.004
κ_4	0.263**	0.210**	0.118**
p-value	0.000	0.000	0.010
κ_5	−0.304**	−0.270**	−0.068
p-value	0.000	0.000	0.111
κ_6	−0.147**	−0.137**	−0.120**
p-value	0.000	0.000	0.001
κ_7	0.290**	0.280**	−0.070**
p-value	0.000	0.000	0.004
κ_8	−0.177**	−0.189**	0.119**
p-value	0.000	0.001	0.001
κ_9	−0.106**	−0.127**	−0.101**
p-value	0.003	0.000	0.001
κ_{10}	−0.098**	0.101**	−0.048**
p-value	0.000	0.001	0.001
κ_{11}	0.192**	−0.143**	0.056
p-value	0.000	0.000	0.059
κ_{12}	−0.095*	0.083**	
p-value	0.015	0.001	
κ_{13}	−0.144**	0.215**	
p-value	0.000	0.000	
κ_{14}	0.094**		
p-value	0.001		
κ_{15}	0.324**		
p-value	0.000		
DOF	8.116**	6.815**	7.139**
p-value	0.000	0.000	0.000
LS		−0.034	
p-value		0.119	
LL	−6823.617	−7094.090	−6875.084

Note. LL means the log-likelihood value, DOF indicates the degrees of freedom parameter of Student-*t* or skew-*t* distribution errors, and LS indicates the log value of skewness parameter, respectively. ** and * indicate the 1% and 5% statistical significance levels. § (§§) indicates the extended EGARCH model with Student-*t* (skew-*t*) distribution errors. For brevity, estimation results for mean equations are not reported.

5. Results

5.1 Model Selections and Estimations

This section documents our results of model selections and estimations. First, we report that our likelihood ratio (LR) tests evidence as follows. First, the EGARCH model with Student-*t* errors is better than that with normal distribution errors for all the three countries. Second, the EGARCH model with skew-*t* errors is better than that with Student-*t* errors for Sweden, while the EGARCH model with Student-*t* errors is better than that with skew-*t* errors for the UK and Switzerland. Third, our further LR tests based on this second evidence clarify that the EGARCH model with skew-*t* errors considering return jumps is better than that with skew-*t* errors ignoring return jumps for Sweden, and the EGARCH model with Student-*t* errors and considering return jumps is better than that with Student-*t* errors ignoring return jumps for the UK and Switzerland.

That is, our LR test results find that the best model to derive the volatilities for Swedish banking sector stock returns is the EGARCH model with skew-*t* errors, which takes bidirectional return jumps into consideration. In addition, our LR test results also find that the best model to derive the volatilities for the UK and Swiss banking sector stock returns is the EGARCH model with Student-*t* errors, which takes bidirectional return jumps into account.

We next argue the model estimation results. Table 2 exhibits the estimation results for our several EGARCH models. That is, the EGARCH model with normal distribution errors (Panel A), the EGARCH model with only Student-*t* or skew-*t* errors (Panel B), and the EGARCH model with Student-*t* or skew-*t* errors and considering bidirectional return jumps (Panel C).

First, as Panels A−C shows, in the EGARCH models with normal, Student-*t*, and skew-*t* distribution errors, the parameter estimates of ARCH effect (ψ), GARCH effect (ϕ), and volatility asymmetry effect (χ) are always all statistically significant. In addition, as Panels B and C indicate, the parameter estimates for the degrees of freedom (DOF) for Student-*t* and skew-*t* densities are always statistically significant with smaller values. Further, Panel B also indicates that the estimated log value of skewness (LS) parameter is also statistically significant. Hence, these results evidence the effectiveness of incorporating the heavy-tailed Student-*t* density or skewed and heavy-tailed skew-*t* density into our extended EGARCH models to capture the fat tails or fat tails and skewness of the three countries' banking sector stock returns.

Moreover, Panel C of Table 2 further evidence that most of the dummy variable parameter estimates of bidirectional return jumps for the three countries are statistically significant. Hence, this clearly evidences the effectiveness of considering bidirectional return jumps for modeling the banking stock return volatilities of the UK, Sweden, and Switzerland.

Table 3. Explanatory power of tail risks in European non-euro banking sectors

	UK[§]	Sweden[§§]	Switzerland[§]
Panel A. 95%VaR			
EGARCH with normal distribution errors			
β	0.021**	0.020**	0.027**
z-statistic	12.619	9.253	12.782
p-value	0.000	0.000	0.000
MR^2	0.093	0.049	0.097
EGARCH with Student-t or skew-t errors			
β	0.021**	0.019**	0.027**
z-statistic	12.606	9.242	12.751
p-value	0.000	0.000	0.000
MR^2	0.093	0.049	0.097
EGARCH with Student-t or skew-t errors and considering bidirectional return jumps			
β	0.023**	0.016**	0.024**
z-statistic	14.118	9.415	13.547
p-value	0.000	0.000	0.000

MR^2	0.119	0.050	0.108
Panel B. 98%VaR			
EGARCH with normal distribution errors			
β	0.020**	0.018**	0.025**
z-statistic	9.346	6.377	9.280
p-value	0.000	0.000	0.000
MR^2	0.100	0.047	0.100
EGARCH with Student-t or skew-t errors			
β	0.020**	0.017**	0.024**
z-statistic	9.367	6.379	9.204
p-value	0.000	0.000	0.000
MR^2	0.100	0.047	0.099
EGARCH with Student-t or skew-t errors and considering bidirectional return jumps			
β	0.021**	0.016**	0.021**
z-statistic	10.366	7.222	9.674
p-value	0.000	0.000	0.000
MR^2	0.126	0.059	0.107
Panel C. 99%VaR			
EGARCH with normal distribution errors			
β	0.017**	0.017**	0.024**
z-statistic	6.741	4.862	7.518
p-value	0.000	0.000	0.000
MR^2	0.088	0.046	0.113
EGARCH with Student-t or skew-t errors			
β	0.017**	0.016**	0.024**
z-statistic	6.747	4.865	7.478
p-value	0.000	0.000	0.000
MR^2	0.088	0.046	0.112
EGARCH with Student-t or skew-t errors and considering bidirectional return jumps			
β	0.019**	0.015**	0.020**
z-statistic	7.908	5.487	7.926
p-value	0.000	0.000	0.000
MR^2	0.125	0.057	0.123

Note. MR^2 indicates the McFadden R-squared value from probit models. ** indicates the 1% statistical significance level. For the results other than 'EGARCH with normal distribution errors,' § (§§) indicates the explanatory power testing of the estimated volatilities from the EGARCH models with Student-*t* (skew-*t*) distribution errors and with or without taking bidirectional return jumps into account.

5.2 Tail Risk Explanatory Power

Table 3 displays the results from our probit models. As Panels A−C show, all the z-statistics and McFadden R-squared values (MR^2) record the highest values for the estimated volatilities from the EGARCH models with Student-*t* or skew-*t* errors and considering bidirectional return jumps. We note that there is no exception for the results. Therefore, for the three countries' banking sectors, the volatility estimates from our extended EGARCH models with Student-*t* or skew-*t* errors and considering bidirectional return jumps show the greatest explanatory power of tail risks measured by VaRs.

This clearly indicates the effectiveness of taking bidirectional return jumps into consideration to capture the tail risks more accurately in the European non-euro banking sectors of the UK, Sweden, and Switzerland. Thus importantly, ignoring bidirectional return jumps will underestimate the volatility levels in plunging banking sector stock prices and undervalue their tail risks. We therefore should pay much more attention to the significant amplifications in international banking sector stock volatilities, especially when significant shocks cause large return jumps and breaks in international stock markets.

6. Conclusions

This study analyzed the nexuses between stock return jumps, volatilities, and tail risks in the European non-euro banking sectors of the UK, Sweden, and Switzerland. Our rigorous quantitative examinations derived the following significant new findings. First, in extending EGARCH models, taking bidirectional stock return jumps into consideration is always effective for all the three countries' banking sectors. Second, in extending EGARCH models, to incorporate both bidirectional stock return jumps and the skew-*t* or Student-*t* density simultaneously is particularly meaningful for all the three countries' banking sectors.

In addition, our results from probit models evidenced that when taking bidirectional stock return jumps into account, the volatility estimates from our extended EGARCH models more accurately capture the tail risks in the three European non-euro banking sector equities. This signifies that if we ignore bidirectional stock return jumps, we will undervalue the levels of tail risks when stock prices of international banking sectors plunge. Hence, we note that this new evidence means how stock return jumps are crucial for tail risk assessment, and this shall be the most significant implications for risk management in international banking sectors, which our rigorous quantitative analysis in the present study derived.

We finally consider that based on the findings and interpretations obtained from our current study, we should engage and derive new further evidence and additional beneficial implications for risk assessment and management in the post-COVID-19 world. These are our next challenges.

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