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Research article

The meaning of structural breaks for risk management: new evidence, mechanisms, and innovative views for the post-COVID-19 era

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Abstract: This paper quantitatively reveals the meaning of structural breaks for risk management by analyzing US and major European banking sector stocks. Applying newly extended Glosten-Jagannathan-Runkle generalized autoregressive conditional heteroscedasticity models, we supply the following new evidence. First, we find that incorporating structural breaks is always effective in estimating banking stock volatilities. Second, we clarify that structural breaks partially explain the tail fatness of banking stock returns. Third, we find that when incorporating structural breaks, the estimated volatilities more accurately capture their downside risk, proving that structural breaks matter for risk management. Fourth, our news impact curve and model parameter analyses also uncover that when incorporating structural breaks, the asymmetry in volatility responses to return shocks is more accurately captured. This proves why the estimated volatilities by incorporating structural breaks better explain downside risk. In addition, we further reveal that the estimated volatilities obtained through incorporating structural breaks increase sharply during momentous events such as the Lehman crisis, the European debt crisis, Brexit, and the recent COVID-19 crisis. Moreover, we also clarify that the volatility spreads between models with and without structural breaks rise during the Lehman and COVID-19 crises. Finally, based on our findings, we derive many significant and beneficial interpretations, implications, and innovative views for risk management using artificial intelligence in the post-COVID-19 era.

Keywords: artificial intelligence; COVID-19; news impact curve; risk management; structural break; volatility

JEL Codes: G01, G15, G21, G32

1. Introduction

Recent shocks associated with COVID-19 strongly remind us of the importance of structural breaks, sharp price drops, and volatility jumps in international stock markets. For instance, in the ten days to March 12, 2020, the FTSE MIB index in Italy fell 32.3%, while to March 18, 2020, the CAC 40 and the DAX 30 indices plummeted 30.0% and 29.3% in France and Germany, respectively. Likewise, in the ten days to March 23, 2020, in the USA and the UK, the S&P 500 and the FTSE 100 indices fell 22.4% and 16.2%, respectively. At the same time, the US volatility index sharply increased by 124.6% to a value of 82.7 over the ten business days until March 16, 2020.

Given these sudden increases in risk in financial markets associated with structural breaks and the importance of the banking industry, to support the soundness of global banking operations, the European Central Bank (2020) and Bank of England (2020) published official statements in March 2020, placing restrictions on Eurozone and UK bank dividend distributions and share buybacks, respectively. Later, in June 2020, the US Federal Reserve Board (2020) issued a press release that also restricted the payout policies of large US banks. Based on these regulatory cautious actions for the banking industries in the US and Europe and the past serious damages on the world economy from the Lehman and European debt crises, which were both caused by the upsets of financial sectors, we understand the particular importance of the US and major European banking sectors for the world economy. To endure sudden increases of risk in the balance sheets in banks, which are caused by their equity capital decreases through large declines of stock returns associated with their structural breaks, the US and major European banking sectors should conduct more proper and cautious risk management and maintain the stabilities of not only the financial sector but also the world economy. Considering these, we ask ourselves the question, how do structural breaks matter for risk management—particularly downside risk management in the US and major European banking sectors? To answer this question, we consider that the best approach is to focus on the US and major European banking sector stock returns and inspect the nexuses between the stock return structural breaks, volatility jumps, and the downside risk in the US and major European banking sectors.

While there are many interesting studies relating to financial risk management (e.g., Buston, 2016; Butaru et al., 2016; Tsuji, 2016; Cardona et al., 2019; Sun et al., 2019; Georgiopoulos, 2020; Pérez-Rodríguez, 2020; Tsuji, 2020; Lv et al., 2021; Malik et al., 2021; Matallín-Sáez et al., 2021) and systemic risk (e.g., Adrian and Boyarchenko, 2018; Varotto and Zhao, 2018; Zeb and Rashid, 2019; Wen et al., 2020; Davydov et al., 2021; Safi et al., 2021; Borri and di Giorgio, 2022), their primary focus is not on structural breaks. Overall, although there are indeed previous studies on structural breaks, few analyze structural breaks in the equity markets of developed countries from the viewpoint of risk management. In addition, while there are extant studies of structural breaks in other assets, they also do not address risk management. These include the studies on exchange rates (Villanueva, 2007; Chowdhury, 2012; Ahmad and Aworinde, 2016), those on interest rates (Maveyraud-Tricoire and Rous, 2009), those on term structure (Bulkley and Giordani, 2011; Esteve et al., 2013), on credit ratings (Xing et al., 2012), and on commodities (Li et al., 2020).

Reviewing research on structural breaks of equities, Granger and Hyung (2004) analyzed structural breaks in S&P 500 absolute returns and their effect on the autocorrelations in the absolute returns, while Ewing and Malik (2005) investigated structural breaks in small and large US firm stock returns and their effect on volatility spillovers between small and large US firm stocks. Subsequently, using panel data analysis, Cerqueti and Costantini (2011) incorporated stock price bubbles in their analysis of structural breaks in OECD countries, Adesina (2017) examined the effect of structural breaks on the volatility persistence of FTSE 100 returns for a period including the Brexit vote, and Smith (2017) estimated US equity premium using a Bayesian model allowing for structural breaks. In addition, Yin (2019) also investigated the US equity premium, again taking structural breaks into consideration.

As discussed, there is currently little research on the meaning of structural breaks in downside risk management, even though there is a clear connection between structural breaks, stock price plunges, and volatility jumps. Considering this, our motivation in this paper is to uncover the meaning of structural breaks for downside risk management in the banking industry. That is, again, as the US Federal Reserve Board, the European Central Bank, and the Bank of England have all published notes to maintain the soundness of the banking industry and given the banking sector is a core financial sector and critical for the entire economy, the impact of structural breaks on downside risk management in the US and major European banking sectors is a matter of great importance.

The goal of this study is to reveal how structural breaks matter for downside risk management in the US and major European banking sectors. To perform robust analysis for this purpose, we apply newly extended econometric models, i.e., a Glosten-Jagannathan-Runkle generalized autoregressive conditional heteroscedasticity (GJR-GARCH) model (Glosten et al., 1993) incorporating structural breaks and Student-*t* errors, to significant banking sector stock return data of the USA, the UK, Germany, and France because our focus in this study is on the nexuses between structural breaks, volatility jumps, and the downside risk in the US and major European banking sectors as we emphasized. We also consider that our results derived from this study should be highly useful since they are all applicable to not only other industries but also overall stock markets around the world.

Specifically, our research questions are as follows. First, are the estimated volatilities taking structural breaks into account effectual for downside risk management? Second, why are such volatilities effective and what are the mechanisms for these volatilities to be effectual? Furthermore, what implications and innovative views can we derive from our results for risk management in the post-COVID-19 era? By clarifying these matters, our quantitative examinations look to enrich our knowledge of the meaning of structural breaks for risk management. We emphasize that to our best knowledge, this is the first multipronged and thorough study to reveal not only how but also why structural breaks are important for downside risk management by supplying ample and robust new evidence alongside the rich interpretations, implications, and innovative views for the post-COVID-19 world.

As a result of our analysis, this study makes many significant contributions to the body of literature. First, the likelihood ratio (LR) tests of our extended GJR-GARCH models robustly show that for all the four countries, incorporating structural breaks in volatility estimations is always effective. This new finding is a worthwhile and robust contribution. Second, our extended GJR-GARCH estimations signify that structural breaks partially explain the tail fatness of international banking stock returns. This means that incorporating structural breaks and the Student-*t* density into GARCH models simultaneously is important when modeling international banking sector stock volatilities. This new evidence is also our significant contribution.

Third, our results from probit and logit models prove that when incorporating structural breaks, the estimated volatilities from our extended GJR-GARCH models more strongly capture the downside risk measured by both Value at Risk (VaR) (e.g., Duffie and Pan, 1997) and Expected Shortfall (ES) (Rockafellar and Uryasev, 2000). This means that if we ignore structural breaks, we could underestimate the volatilities when international banking stock prices fall. This is also a valuable contribution, showing how structural breaks are crucial for downside risk management. Fourth, our results show that when incorporating structural breaks, the computed news impact curves (NICs) (Engle and Ng, 1993) from our extended GJR-GARCH more accurately capture the asymmetry in international banking stock volatility responses to their return shocks. This explains why the estimated volatilities from our extended models with structural breaks more accurately explain the downside risk, and this new finding also provides a contribution from our analysis.

Besides, we find that when incorporating structural breaks, the estimated asymmetry parameters in our extended GJR-GARCH evaluate volatility asymmetry to be much larger. This also shows why incorporating structural breaks matters in volatility estimation to capture the downside risk more accurately, and this new evidence also signifies the novelty of our study. Moreover, we further find that our estimated international banking sector stock volatilities from our extended models with structural breaks rise sharply at the time of economically and financially momentous events such as the Lehman crisis, the European debt crisis, Brexit, and the recent COVID-19 crisis. This clearly demonstrates why the estimated volatilities from our extended models with structural breaks more precisely capture the downside risk, and this is also our significant contribution.

In addition, we furthermore evidence that our computed volatility spreads between the volatilities from our extended models with structural breaks and those from the corresponding models without structural breaks rise during the Lehman and COVID-19 crises, when international banking sector stock prices particularly plunged, and their volatilities particularly rose. This is the newly found mechanism that including structural breaks is highly effective for capturing the downside risk accurately, and this clarification also shows the novelty of this study.

Finally, in addition to the above, we further present many detailed and highly beneficial interpretations, implications, and innovative views for risk management in the post-COVID-19 era; and this is an added and valuable novel contribution of our research. Overall, the contributions of this paper not only present much new evidence of the effectiveness of structural breaks in capturing downside risk but also clarify the mechanisms that explain both how and why structural breaks matter for risk management. Again, we note that our contributions also include the derivation of new significant interpretations, implications, and innovative views for risk management in the post-COVID-19 world. Therefore, we consider that our overall contribution is even stronger and highly novel. The rest of the paper is organized as follows. Section 2 explains the data, Section 3 presents our models, and Section 4 describes our results. Section 5 discusses how structural breaks matter for risk management, and Section 6 argues why structural breaks matter for risk management. Section 7 provides significant interpretations and implications with some innovative views for the post-COVID-19 world, and Section 8 concludes the paper.

2. Data

Given the importance as we discussed, this study analyzes the daily returns of banking sector stock price indices of the USA, the UK, Germany, and France. The four index data we use in this study are all in local currency terms as constructed by Thomson Reuters. Specifically, the USA in US dollars; the UK in UK pounds; and Germany and France in euros. Again, we consider that downside risk is particularly important for the banking industry, and in the global economy, the banking sectors of these countries are highly crucial. Thus, our choice of the four international banking sectors is quite appropriate and meaningful for analyzing downside risk and the meaning of structural breaks. Using the four banking sector index prices of p_t (prices at time t) and p_{t-1} (prices at time $t-1$), we compute the daily log difference percentage returns as ln $(p_t/p_{t-1}) \times 100$. We use daily data because this is common in the prevailing academic research (e.g., Mensi et al., 2019; Abakah et al., 2020) and the frequency of most interest to industry practitioners given rapid dynamic price evolution in recent integrating international stock markets.

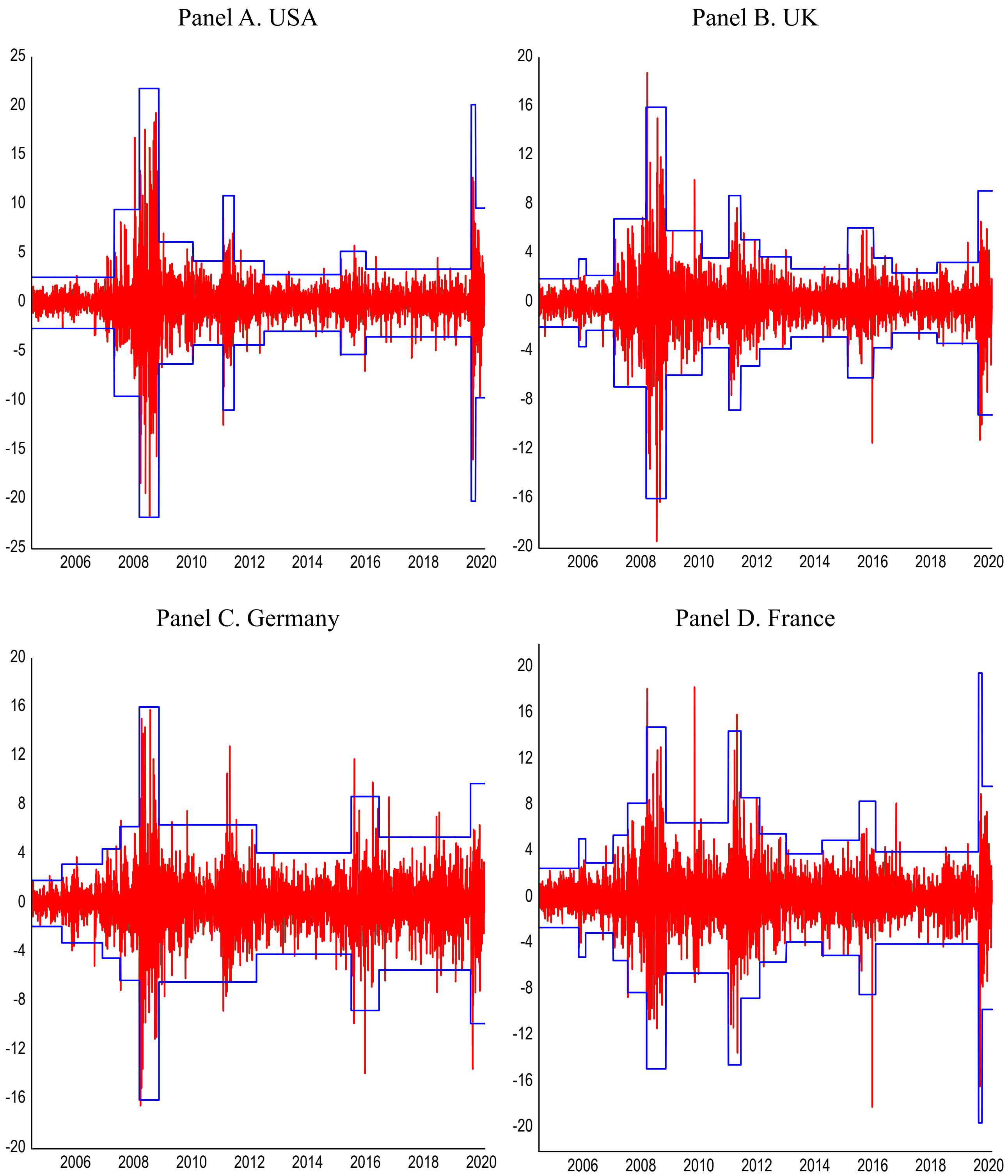

Figure 1. Structural breaks in log percentage returns of international banking stocks.

Note: Bands of ±3 standard deviations and change points identified by the iterated cumulative sums of squares algorithm.

Figure 1 plots the time-series evolution of the four banking sector stock returns including the ±3 standard deviation bands to help show the structural breaks, which we find using the iterated cumulative sums of squares (ICSS) algorithm. We note that the ICSS algorithm is a very reliable methodology for identifying structural breaks (e.g., Ewing and Malik, 2005, 2016; Tsuji, 2020). In addition, Table 1 details the number of structural breaks for the four international banking stock returns, showing many structural breaks particularly for the UK and France. These return characteristics clearly show the importance of taking structural breaks into account when analyzing these series.

The sample period for the time-series returns we analyze is from January 4, 2005 to August 10, 2020, comprising 4070 observations for each series. We specify this sample period as it includes both the earlier Lehman and European debt crises and the more recent effects of Brexit and COVID-19. We note that the Lehman crisis is a particularly momentous event, which caused large and multiple structural breaks as demonstrated in Figure 1. Thus including the Lehman crisis period is highly meaningful for our study. This enables us to compare the effects of structural breaks during the periods of the Lehman and European debt crises, Brexit, and the COVID-19 crisis, and this is also beneficial for our study.

Table 2 supplies descriptive statistics for the four banking stock returns. As shown, all exhibit slightly negative mean returns, and all the returns have negative values for skewness. Furthermore, the values of kurtosis for all the returns exceed three, i.e., the kurtosis of normal distributions, thereby showing that all the series have fat tails. Table 2 also shows that Jarque-Bera statistics strongly reject the normality of all the series. These return characteristics imply the necessity of incorporating fat-tailed and skewed distributions into quantitative models when analyzing these series. Likewise, the augmented Dickey–Fuller tests in Table 2 strongly reject the null hypothesis of a unit root, indicating that all the return series are stationary.

Table 1. Number of structural breaks for international banking stock returns.

USA	UK	Germany	France
11	15	9	15

Note: Structural breaks identified by the iterated cumulative sums of squares algorithm.

Table 2. Summary statistics for international banking stock returns.

	USA	UK	Germany	France
Mean	−0.009	−0.039	−0.051	−0.020
SD	2.275	1.856	2.131	2.262
Skewness	−0.011	−0.262	−0.147	−0.095
Kurtosis	19.805	17.341	11.189	11.565
JB	47890.08	34925.30	11387.05	12446.28
p-value	0.000	0.000	0.000	0.000
ADF	−30.228	−62.186	−61.002	−61.323
p-value	0.000	0.000	0.000	0.000

Note: Statistics are for log difference daily percentage returns with 4070 observations for each series. SD—standard deviation; JB—Jarque–Bera statistic; ADF—augmented Dickey–Fuller test statistic.

3. Extended GJR-GARCHs

To obtain precise evidence on the effects of structural breaks, we employ the GJR-GARCH model, and we attempt to extend this to incorporate structural breaks and fat-tailed or skewed and fat-tailed densities. We employ the GJR model because this model readily captures the asymmetric feature of volatility. As the exponential GARCH (EGARCH) model also has this favorable characteristic, we also examined by using similarly extended EGARCH models; and the results were much the same. We thus report the results only from our extended GJR-GARCH models in this paper. Furthermore, given we have carefully determined our analyzing sample period, we conduct robustness checks using probit and logit models and two risk measures of VaR and ES as described later without altering our sample period.

First, the GJR-GARCH model without structural breaks is specified as follows:

$$r_t = \xi_0 + \sum_{i=1}^{p} \xi_i r_{t-i} + \varepsilon_t, \tag{1}$$

$$h_t = \omega + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2 + \gamma S_{t-1}^- \varepsilon_{t-1}^2. \tag{2}$$

In the mean equation of Equation (1), r_t is each country's banking sector stock return at time t, r_{t-i} is the i-th lag of each country's banking sector stock return, ε_t is the error term, p is the autoregressive (AR) order, and we determine the AR lag orders using the Bayesian information criterion. Further, ξ_0 is the constant term and ξ_i is the coefficient of r_{t-i}. For the error term ε_t, besides normal distribution errors, we also examine Student-t and skew-t distribution errors to allow for the fat-tailed or skewed and fat-tailed distributions.

When applying Student-t errors, the errors (return residuals) in Equation (1) are governed by the degrees of freedom (DOF) parameter v, where a smaller v indicates a fatter-tailed distribution, while when $v \to \infty$, it approaches a normal distribution. Alternatively, when applying skew-t errors, the return residuals are governed by the DOF parameter and a skewness parameter, where a smaller v again signifies a fatter-tailed distribution (Bauwens and Laurent, 2005; Tsuji, 2018).

In the variance equation of Equation (2), h_t (h_{t-1}) is each country's banking sector stock return's variance at time t ($t-1$), ε_{t-1}^2 is the squared one-day lag of the return residual, and $S_{t-1}^- = 1$ if $\varepsilon_{t-1} < 0$ and 0 otherwise. Further, ω is the constant term, β is the coefficient of h_{t-1}, α is the coefficient of ε_{t-1}^2, and γ is the coefficient of $S_{t-1}^- \varepsilon_{t-1}^2$.

Next, we specify the GJR-GARCH model with structural breaks as follows:

$$r_t = \xi_0 + \sum_{i=1}^{p} \xi_i r_{t-i} + \varepsilon_t,$$

$$h_t = \omega + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2 + \gamma S_{t-1}^- \varepsilon_{t-1}^2 + \sum_{i=1}^{k} d_i D_{i,t}. \tag{3}$$

The mean equation is the same as Equation (1), and the only difference between Equations (2) and (3) as the variance equation is the presence of $\sum_{i=1}^{k} d_i D_{i,t}$, where $D_{i,t}$ are dummy variables for the structural breaks such that $D_{i,t} = 1$ from the i-th structural break point onwards and 0 elsewhere, k is the number of structural breaks, and d_i is the coefficient of $D_{i,t}$. The other notations in Equation (3) are the same as those in Equation (2). In Equations (2) and (3), α always captures the so-called autoregressive conditional heteroscedasticity (ARCH) effect, or the effect of the return shocks on volatility, β depicts the so-called GARCH effect signifying volatility persistence, and γ describes the asymmetric effects of the return shocks on volatility.

4. Results

This section presents the results of our model selections and estimations. We first examine the GJR models by considering normal, Student-*t*, and skew-*t* distribution errors and structural breaks using LR tests. We then discuss the model estimation results.

4.1. LR tests

Table 3 provides the LR test results for our extended GJR-GARCH models. The null hypothesis in Panel A is that the GJR model with normal distribution errors is superior to the GJR model with Student-*t* errors. The null hypothesis in Panel B is that the GJR model with Student-*t* errors is superior to the GJR model with skew-*t* errors. The null hypothesis in Panel C is that the GJR model with Student-*t* errors but without structural breaks is superior to the GJR model with Student-*t* errors and structural breaks. We note that in Panel C, we test the GJR model of Student-*t* errors with or without structural breaks based on the model selection results in Panel B.

As shown in Panel A of Table 3, we reject the null hypothesis for all the models, meaning that in all the four countries, the GJR model with Student-*t* errors is superior to the GJR model with normal distribution errors. Next, as shown in Panel B of Table 3, for all the models, we cannot reject the null hypothesis. This means that the GJR model with Student-*t* errors is superior to that with skew-*t* errors for all the four countries.

Table 3. Results of likelihood ratio tests for GJR models.

	USA	UK	Germany	France
Panel A. Student-*t* vs. normal				
Statistic	270.443**	164.037**	235.839**	157.974**
p-value	0.000	0.000	0.000	0.000
Panel B. Skew-*t* vs. Student-*t*				
Statistic	1.327	1.278	2.773	1.804
p-value	0.249	0.258	0.096	0.179
Panel C. Student-*t* with structural breaks vs. Student-*t* without structural breaks				
Statistic	87.849**	119.278**	66.084**	81.929**
p-value	0.000	0.000	0.000	0.000

Note: The test statistic follows a χ^2 distribution. In Panel A, the null hypothesis is that the GJR model with normal distribution errors is superior to the GJR model with Student-*t* errors. In Panel B, the null hypothesis is that the GJR model with Student-*t* errors is superior to the GJR model with skew-*t* errors. In Panel C, the null hypothesis is that the GJR model with Student-*t* errors but without structural breaks is superior to the GJR model with Student-*t* errors and structural breaks. ** denotes the rejection of the null hypothesis at the 5% significance level.

Finally, as shown in Panel C of Table 3, we reject the null hypothesis for all the models, suggesting that in all the four countries, incorporating structural breaks is always effective. That is, our LR tests find that the best model is the GJR model with Student-*t* errors and structural breaks for all the four countries of the USA, the UK, Germany, and France.

4.2. Model estimations

Table 4 provides the estimation results for our extended GJR models. Panel A details the results for the GJR models with normal distribution errors for all the four countries, and Panel B details the results for the GJR models with Student-*t* errors for all the four countries. Lastly, Panel C details the results for the GJR models with structural breaks and Student-*t* errors for all the four countries.

As shown in Panel A, in the GJR models with normal distribution errors, the estimated ARCH α, GARCH β, and volatility asymmetry γ parameters are all statistically significant. In Panel B, in the GJR models with Student-*t* errors, the estimates of α, β, and γ are again all statistically significant. Panel B also shows that the parameter estimates of the DOF for Student-*t* errors v are all statistically significant, with values ranging from 4.969 (USA) to 7.603 (France). These smaller values demonstrate the importance of considering the fat tails of all four banking stock returns and the effectiveness of incorporating heavy-tailed Student-*t* densities into our extended GJR models.

In Panel C, once again, all of the GARCH effect β and the volatility asymmetry γ parameters are statistically significant. Panel C also shows that the parameter estimates of the DOF for Student-*t* errors v are again statistically significant, with values ranging from 5.524 (USA) to 8.558 (France), yet again proving the effectiveness of incorporating Student-*t* densities into our GJR models to capture the fat tails of all four banking stock returns.

In addition, Panel C further shows that most of the estimates of the dummy variable parameters for structural breaks d_i are statistically significant, and this likewise supports the effectiveness of incorporating structural breaks into our models. We also note that all the parameter values of v in Panel C are a little larger than the corresponding values in Panel B, suggesting that the structural break dummy variables partially explain the fat tails of four banking stock returns, newly showing the importance of structural breaks in capturing the fat tails of banking stock returns.

Table 4. Estimation results for the GJR models with normal and Student-*t* errors without structural breaks and the GJR models with Student-*t* errors and structural breaks.

	USA	UK	Germany	France
Panel A. GJR with normal distribution errors				
ω	0.029**	0.015**	0.023**	0.036**
p-value	0.000	0.000	0.000	0.000
α	0.042**	0.042**	0.033**	0.031**
p-value	0.000	0.000	0.000	0.000
β	0.893**	0.913**	0.932**	0.908**
p-value	0.000	0.000	0.000	0.000
γ	0.117**	0.087**	0.060**	0.113**
p-value	0.000	0.000	0.000	0.000
LL	−7183.327	−6968.934	−7964.220	−8070.028
Panel B. GJR with Student-*t* errors				
ω	0.019**	0.017**	0.015**	0.034**
p-value	0.000	0.000	0.003	0.000
α	0.039**	0.029**	0.036**	0.021*
p-value	0.000	0.003	0.000	0.011
β	0.905**	0.917**	0.927**	0.915**
p-value	0.000	0.000	0.000	0.000
γ	0.116**	0.102**	0.076**	0.118**
p-value	0.000	0.000	0.000	0.000
v	4.969**	6.513**	5.634**	7.603**
p-value	0.000	0.000	0.000	0.000
LL	−7048.106	−6886.916	−7846.301	−7991.041
Panel C. GJR with Student-*t* errors and structural breaks				
ω	0.053**	0.083**	0.029**	0.128**
p-value	0.000	0.000	0.000	0.000
α	0.018	−0.006	0.025**	0.006
p-value	0.052	0.567	0.007	0.520
β	0.818**	0.765**	0.871**	0.781**
p-value	0.000	0.000	0.000	0.000
γ	0.157**	0.143**	0.095**	0.152**
p-value	0.000	0.000	0.000	0.000
d_1	0.843**	0.127*	0.024*	0.295**
p-value	0.001	0.020	0.014	0.006
d_2	4.352*	−0.116*	0.096*	−0.268*
p-value	0.011	0.043	0.017	0.013
d_3	−4.811**	0.778**	0.132	0.303**
p-value	0.008	0.000	0.102	0.008
d_4	−0.181*	3.357**	1.199**	0.626**
p-value	0.018	0.000	0.001	0.003
d_5	1.043*	−3.546**	−1.274**	2.089**

Continued on next page

	USA	UK	Germany	France
Panel C. GJR with Student-*t* errors and structural breaks				
p-value	0.024	0.000	0.000	0.002
d_6	−1.079*	−0.393**	−0.072**	−2.599**
p-value	0.019	0.000	0.010	0.000
d_7	−0.117**	1.334**	0.329**	2.883**
p-value	0.006	0.003	0.001	0.000
d_8	0.152**	−1.061*	−0.264**	−2.220**
p-value	0.003	0.013	0.005	0.000
d_9	−0.138**	−0.278**	0.379*	−0.707**
p-value	0.004	0.001	0.026	0.000
d_{10}	5.029*	−0.126**		−0.254**
p-value	0.016	0.002		0.001
d_{11}	−4.050*	0.337**		0.111*
p-value	0.043	0.000		0.038
d_{12}		−0.213*		0.312*
p-value		0.013		0.038
d_{13}		−0.165**		−0.449**
p-value		0.000		0.004
d_{14}		0.097**		6.284*
p-value		0.001		0.012
d_{15}		1.317**		−4.904*
p-value		0.000		0.045
v	5.524**	8.097**	6.230**	8.558**
p-value	0.000	0.000	0.000	0.000
LL	−7004.181	−6827.277	−7813.259	−7950.077

Note: LL indicates the log-likelihood value. ** and * denote the 1% and 5% significance levels, respectively. For brevity, estimation results of mean equations are not reported.

5. How do structural breaks matter for risk management?

This section considers how structural breaks matter for risk management by examining the explanatory power for downside risk of our volatility estimates from our extended GJR-GARCH models. To do this, we employ probit and logit models and test the following annualized volatilities $\sigma_t^{Student\text{-}t\_SB} = \sqrt{\hat{h}_t^{Student\text{-}t\_SB}} \times \sqrt{252}$, $\sigma_t^{Student\text{-}t} = \sqrt{\hat{h}_t^{Student\text{-}t}} \times \sqrt{252}$, and $\sigma_t^{normal} = \sqrt{\hat{h}_t^{normal}} \times \sqrt{252}$, where $\hat{h}_t^{Student\text{-}t\_SB}$, $\hat{h}_t^{Student\text{-}t}$, and $\hat{h}_t^{normal}$ are the daily variance estimates from the GJR-GARCH models with Student-*t* errors and structural breaks, with Student-*t* errors but without structural breaks, and with normal distribution errors but without structural breaks, respectively. Because we inspect the explanatory power of estimated volatilities for downside risk, we first compute tail risk by VaR and ES, and then using probit and logit models, we test the explanatory power of estimated volatilities for the tail risk measured by VaR or ES as in Tsuji (2016).

5.1. VaR

First, applying probit and logit models and using VaRs, we test the downside risk explanatory power of our volatility estimates as follows:

$$\Delta p_t = \kappa + \lambda x_t + \tau_t,$$

$$y_t = \begin{cases} 1 & \text{if } \Delta p_t \leq k\%\text{VaR} \\ 0 & \text{if } \Delta p_t > k\%\text{VaR} \end{cases}, \tag{4}$$

where Δp_t denotes the price change in each country's banking sector stock index, k takes a value of 95, 98, or 99, and x_t is each of our volatility estimates, $\sigma_t^{Student\text{-}t\_SB}$, $\sigma_t^{Student\text{-}t}$, or σ_t^{normal}.

In addition, $\Delta p_t \leq k\%$VaR means that Δp_t negatively exceeds $k\%$VaR. Thus, this probit or logit model setting in Equation (4) enables us to test the explanatory power of volatility estimates for downside risk in banking sector stocks. Note that a positive coefficient λ indicates the downside risk explanatory power of the volatility estimates.

5.1.1. Results from probit models

Table 5 shows the results of probit models for the explanatory power of VaRs. Panels A, B, and C provide the results for 95%VaR, 98%VaR, and 99%VaR, respectively. Explaining the results for the volatilities from our extended GJR models, in Panels A–C, all the z-statistics and McFadden R-squared (M-R^2) values are the highest for the volatilities from the GJR models with structural breaks and Student-t errors in the three GJR models. That is, in all the cases, the estimated volatilities from the GJR models with structural breaks and Student-t errors show the highest explanatory power of downside risk measured by the VaRs. This demonstrates the effectiveness of considering structural breaks to capture the downside risk more accurately in banking sector stocks of the USA, the UK, Germany, and France.

Table 5. VaR explanatory power: results from probit models.

	USA	UK	Germany	France
Panel A. 95%VaR				
GJR with normal distribution errors				
λ	0.014**	0.018**	0.011**	0.014**
z-statistic	13.727	12.334	6.376	10.096
p-value	0.000	0.000	0.000	0.000
M-R^2	0.109	0.088	0.024	0.060
GJR with Student-t errors				
λ	0.014**	0.018**	0.010**	0.014**
z-statistic	13.800	12.231	6.451	10.063
p-value	0.000	0.000	0.000	0.000
M-R^2	0.110	0.086	0.024	0.059

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	USA	UK	Germany	France
GJR with Student-*t* errors and structural breaks				
λ	0.014**	0.022**	0.011**	0.016**
z-statistic	14.494	13.949	6.455	11.022
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.122	0.116	0.024	0.071
Panel B. 98%VaR				
GJR with normal distribution errors				
λ	0.014**	0.017**	0.013**	0.015**
z-statistic	10.571	9.046	6.142	8.128
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.128	0.091	0.044	0.076
GJR with Student-*t* errors				
λ	0.013**	0.016**	0.012**	0.015**
z-statistic	10.526	9.005	6.263	8.086
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.127	0.090	0.045	0.075
GJR with Student-*t* errors and structural breaks				
λ	0.013**	0.020**	0.014**	0.016**
z-statistic	11.183	10.186	6.632	8.688
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.145	0.120	0.051	0.087
Panel C. 99%VaR				
GJR with normal distribution errors				
λ	0.014**	0.015**	0.013**	0.015**
z-statistic	9.243	6.620	5.187	6.791
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.173	0.083	0.052	0.092
GJR with Student-*t* errors				
λ	0.014**	0.015**	0.012**	0.015**
z-statistic	9.175	6.552	5.300	6.732
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.171	0.081	0.055	0.090
GJR with Student-*t* errors and structural breaks				
λ	0.014**	0.019**	0.014**	0.015**
z-statistic	9.643	7.772	5.637	7.105
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.193	0.120	0.062	0.101

Note: $M\text{-}R^2$—McFadden *R*-squared value. ** denotes the 1% significance level. For the results other than 'GJR with normal distribution errors,' the test results for the explanatory power of the estimated volatilities from the models of Student-*t* errors with or without structural breaks are shown.

Table 6. VaR explanatory power: results from logit models.

	USA	UK	Germany	France
Panel A. 95%VaR				
GJR with normal distribution errors				
λ	0.026**	0.033**	0.022**	0.028**
z-statistic	13.961	12.401	6.872	10.472
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.101	0.080	0.024	0.057
GJR with Student-t errors				
λ	0.026**	0.033**	0.021**	0.028**
z-statistic	14.066	12.281	6.945	10.439
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.103	0.079	0.025	0.057
GJR with Student-t errors and structural breaks				
λ	0.026**	0.041**	0.022**	0.030**
z-statistic	14.711	13.909	6.937	11.332
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.114	0.108	0.025	0.069
Panel B. 98%VaR				
GJR with normal distribution errors				
λ	0.028**	0.033**	0.029**	0.031**
z-statistic	11.039	9.302	6.863	8.389
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.120	0.082	0.045	0.070
GJR with Student-t errors				
λ	0.027**	0.033**	0.027**	0.030**
z-statistic	10.988	9.245	6.992	8.341
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.119	0.081	0.047	0.069
GJR with Student-t errors and structural breaks				
λ	0.028**	0.041**	0.031**	0.033**
z-statistic	11.642	10.353	7.371	8.976
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.137	0.110	0.052	0.081
Panel C. 99%VaR				
GJR with normal distribution errors				
λ	0.032**	0.033**	0.031**	0.034**
z-statistic	9.607	6.907	5.742	7.212
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.161	0.075	0.053	0.087

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	USA	UK	Germany	France
GJR with Student-*t* errors				
λ	0.031**	0.032**	0.030**	0.034**
z-statistic	9.515	6.821	5.865	7.145
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.160	0.073	0.055	0.085
GJR with Student-*t* errors and structural breaks				
λ	0.032**	0.041**	0.034**	0.036**
z-statistic	9.983	8.093	6.220	7.608
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.183	0.110	0.062	0.097

Note: $M\text{-}R^2$—McFadden *R*-squared value. ** denotes the 1% significance level. For the results other than "GJR with normal distribution errors", the test results for the explanatory power of the estimated volatilities from the models of Student-*t* errors with or without structural breaks are shown.

5.1.2. Results from logit models

Table 6 provides the results of logit models for the explanatory power of VaRs, and this serves as a robustness check for the preceding findings. Panels A, B, and C present the results of the 95%VaR, 98%VaR, and 99%VaR, respectively. Documenting the results for the volatilities from our extended GJR models, in Panels A−C, all the *z*-statistics and $M\text{-}R^2$ are again the highest for the volatilities from the GJR models with structural breaks and Student-*t* errors in the three GJR models except for the case of the 95%VaR for Germany.

Hence again, the estimated volatilities from the GJR models with structural breaks and Student-*t* errors have the greatest explanatory power of downside risk when measured by VaRs. Thus, this much robustly proves the effectiveness of taking structural breaks into consideration to capture the downside risk for the four countries' banking sectors more precisely.

5.2. ES

Next, using probit and logit models and ES values, we test the downside risk explanatory power of our volatility estimates as follows:

$$\Delta p_t = \kappa + \lambda x_t + \tau_t,$$

$$y_t = \begin{cases} 1 & \text{if } \Delta p_t \le k\%\text{ES} \\ 0 & \text{if } \Delta p_t > k\%\text{ES} \end{cases}, \tag{5}$$

where Δp_t denotes the price change in each country's banking sector stock index, k takes a value of 95, 98, or 99, and x_t is again each of our volatility estimates, $\sigma_t^{Student\text{-}t\_SB}$, $\sigma_t^{Student\text{-}t}$, or σ_t^{normal}.

Moreover, $\Delta p_t \le k\%\text{ES}$ means that Δp_t negatively exceeds $k\%\text{ES}$. Hence the use of the probit or logit model setting in Equation (5) enables us to examine the explanatory power of the volatility estimates for downside risk in banking sector stocks. Once again, a positive coefficient λ suggests the downside risk explanatory power of the volatility estimates.

5.2.1. Results from probit models

Table 7 presents the results from probit models for the explanatory power of ESs, and this also serves as a robustness check. Panels A, B, and C show the results for the 95%ES, 98%ES, and 99%ES, respectively. Explaining the results for the volatilities from our extended GJR models, in Panels A−C, all of the *z*-statistics and $M\text{-}R^2$ values are higher for the volatilities from the GJR models with structural breaks and Student-*t* errors than the other GJR models without structural breaks.

That is, in all the cases, the estimated volatilities from the GJR models with structural breaks and Student-*t* errors provide the greatest explanatory power of downside risk as measured by the ESs. This again shows the effectiveness of including structural breaks to capture the downside risk more strongly in the banking sectors of all the four countries.

Table 7. Explanatory power of Expected Shortfall: results from probit models.

	USA	UK	Germany	France
Panel A. 95%ES				
GJR with normal distribution errors				
λ	0.013**	0.016**	0.012**	0.014**
z-statistic	10.065	8.627	5.718	7.680
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.120	0.091	0.043	0.075
GJR with Student-*t* errors				
λ	0.013**	0.016**	0.012**	0.014**
z-statistic	10.019	8.583	5.841	7.617
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.119	0.090	0.045	0.073
GJR with Student-*t* errors and structural breaks				
λ	0.013**	0.020**	0.013**	0.016**
z-statistic	10.769	9.725	6.227	8.305
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.139	0.120	0.051	0.089
Panel B. 98%ES				
GJR with normal distribution errors				
λ	0.015**	0.013**	0.014**	0.014**
z-statistic	8.071	5.308	5.197	5.784
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.218	0.072	0.077	0.081
GJR with Student-*t* errors				
λ	0.015**	0.013**	0.013**	0.014**
z-statistic	7.995	5.261	5.260	5.722
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.215	0.071	0.079	0.079

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	USA	UK	Germany	France
GJR with Student-*t* errors and structural breaks				
λ	0.015**	0.017**	0.016**	0.015**
z-statistic	8.332	6.397	5.614	6.312
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.245	0.110	0.091	0.098
Panel C. 99%ES				
GJR with normal distribution errors				
λ	0.015**	0.016**	0.016**	0.012**
z-statistic	6.265	5.541	5.042	3.908
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.239	0.131	0.125	0.069
GJR with Student-*t* errors				
λ	0.015**	0.016**	0.016**	0.012**
z-statistic	6.178	5.500	5.106	3.829
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.234	0.128	0.129	0.066
GJR with Student-*t* errors and structural breaks				
λ	0.015**	0.021**	0.018**	0.014**
z-statistic	6.359	6.398	5.426	4.550
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.265	0.192	0.149	0.095

Note: $M\text{-}R^2$—McFadden *R*-squared value. ** denotes the 1% significance level. For the results other than 'GJR with normal distribution errors,' the test results for the explanatory power of the estimated volatilities from the models of Student-*t* errors with or without structural breaks are shown.

5.2.2. Results from logit models

Table 8 presents the results of logit models for the explanatory power of ESs, which serves as a further robustness check, with Panels A, B, and C exhibiting the results of the 95%ES, 98%ES, and 99%ES, respectively. Documenting the results for the volatilities from our extended GJR models, in Panels A−C, all the *z*-statistics and $M\text{-}R^2$ are higher for the volatilities from the GJR models with structural breaks and Student-*t* errors than those without structural breaks. That is, in all the cases, the estimated volatilities from the GJR models with structural breaks and Student-*t* errors again yield the greatest explanatory power of downside risk as measured by the ESs. This therefore again robustly shows the effectiveness of incorporating structural breaks in capturing the downside risk more precisely.

As discussed, the effectiveness of incorporating structural breaks into econometric models for explaining downside risk is extremely robust. We also note that for the USA, the UK, and France, incorporating structural breaks is always and perfectly effective for precisely capturing their downside risk regardless of the chosen risk measure and the testing model.

Table 8. Explanatory power of Expected Shortfall: Results from logit models.

	USA	UK	Germany	France
Panel A. 95%ES				
GJR with normal distribution errors				
λ	0.027**	0.033**	0.029**	0.031**
z-statistic	10.506	8.904	6.348	7.961
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.112	0.082	0.044	0.069
GJR with Student-t errors				
λ	0.027**	0.033**	0.027**	0.030**
z-statistic	10.455	8.844	6.478	7.890
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.112	0.081	0.046	0.068
GJR with Student-t errors and structural breaks				
λ	0.027**	0.041**	0.031**	0.033**
z-statistic	11.210	9.920	6.887	8.639
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.131	0.109	0.052	0.083
Panel B. 98%ES				
GJR with normal distribution errors				
λ	0.036**	0.032**	0.037**	0.033**
z-statistic	8.311	5.534	5.863	6.171
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.202	0.066	0.078	0.077
GJR with Student-t errors				
λ	0.035**	0.031**	0.034**	0.033**
z-statistic	8.206	5.480	5.941	6.098
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.200	0.064	0.080	0.076
GJR with Student-t errors and structural breaks				
λ	0.036**	0.040**	0.039**	0.035**
z-statistic	8.552	6.731	6.320	6.829
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.230	0.101	0.092	0.094
Panel C. 99%ES				
GJR with normal distribution errors				
λ	0.039**	0.040**	0.044**	0.032**
z-statistic	6.460	5.850	5.688	4.098
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.225	0.120	0.127	0.065

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	USA	UK	Germany	France
GJR with Student-*t* errors				
λ	0.038**	0.039**	0.042**	0.031**
z-statistic	6.340	5.802	5.771	4.010
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.220	0.117	0.131	0.062
GJR with Student-*t* errors and structural breaks				
λ	0.039**	0.050**	0.048**	0.036**
z-statistic	6.562	6.819	6.120	4.900
p-value	0.000	0.000	0.000	0.000
$M\text{-}R^2$	0.252	0.177	0.153	0.090

Note: $M\text{-}R^2$—McFadden *R*-squared value. ** denotes the 1% significance level. For the results other than 'GJR with normal distribution errors,' the test results for the explanatory power of the estimated volatilities from the models of Student-*t* errors with or without structural breaks are shown.

6. Why do structural breaks matter for risk management?

The previous section newly evidenced that our extended GJR-GARCH models incorporating structural breaks more robustly explain downside risk in the four banking sectors. We now ask why incorporating structural breaks is so effective for capturing downside risk accurately and what mechanisms bring about this explanatory power. This section reveals the reasons and the underlying mechanisms by focusing on the (*i*) NICs, (*ii*) model parameter estimates, (*iii*) volatility estimates, and (*iv*) volatility spreads.

6.1. How do structural breaks affect NICs?

We begin by examining the effect of structural breaks on the NICs of our GJR models. We also investigate the effect of the differences in model error distributions on the NICs. First, the NIC of our GJR models without structural breaks is as follows:

$$\begin{cases} h_t = \omega + \beta\sigma^2 + \alpha\varepsilon_{t-1}^2, & \text{for } \varepsilon_{t-1} > 0, \\ h_t = \omega + \beta\sigma^2 + (\alpha+\gamma)\varepsilon_{t-1}^2, & \text{for } \varepsilon_{t-1} < 0, \end{cases} \tag{6}$$

where h_t shows the variance of the GJR model with normal distribution errors or Student-*t* errors, and σ denotes the unconditional volatility. The other notations are the same as those in Equations (1) and (2). Next, the NIC of our GJR models with structural breaks is as follows:

$$\begin{cases} h_t = \omega + \beta\sigma^2 + \alpha\varepsilon_{t-1}^2 + \sum_{i=1}^{k} d_i D_{i,t}, & \text{for } \varepsilon_{t-1} > 0, \\ h_t = \omega + \beta\sigma^2 + (\alpha+\gamma)\varepsilon_{t-1}^2 + \sum_{i=1}^{k} d_i D_{i,t}, & \text{for } \varepsilon_{t-1} < 0, \end{cases} \tag{7}$$

where h_t shows the variance of the GJR model with structural breaks and Student-*t* errors, and σ denotes the unconditional volatility. The remaining notations are the same as those in Equations (1)−(3).

Figure 2 shows the NICs from our three GJR models, i.e., the GJR with normal distribution errors, with Student-*t* errors, or with structural breaks and Student-*t* errors. Figure 2 shows that all the four NICs of the GJR with structural breaks and Student-*t* errors most strongly respond to negative return shocks. This figure also indicates that all the four NICs have their weakest responses to positive return shocks without exceptions.

Each panel of Figure 2 further shows that the shape of the NICs of the GJR with normal distribution errors and the shape of the NICs of the GJR with Student-*t* errors but without structural breaks are almost the same. This indicates that the responses to both positive and negative return shocks are irrelevant to the model error distributions. That is, incorporating structural breaks enables us to capture the asymmetric feature of return shock impacts on volatilities more precisely, and this leads to explaining the downside risk in banking sector stocks of the four countries more strongly, as evidenced in Tables 5−8.

6.2. How do structural breaks affect model parameter estimates?

We next examine the model parameter estimates. Figure 3 presents the parameter estimates of our three GJR models, i.e., the GJR with normal distribution errors, with Student-*t* errors, or with structural breaks and Student-*t* errors. Figure 3 shows the following unambiguous evidence. First, as shown in Panel B, all the values of the GARCH parameter (β) decrease when structural breaks are incorporated into the GJR models, meaning that volatility persistence should be lower than what the models without structural breaks show. Second, as shown in Panel C, when structural breaks are incorporated, all the values of the asymmetry parameter (γ) increase in the GJR models, signifying that volatility asymmetry should be larger than what the models without structural breaks indicate.

These consistent and clear results shown in Figure 3 robustly demonstrate that incorporating structural breaks leads to capturing both volatility persistence and the asymmetric feature of return shock impacts on volatilities more accurately. Because of these mechanisms, we consider that our GJR models incorporating structural breaks more precisely capture the downside risk, as presented in Tables 5−8.

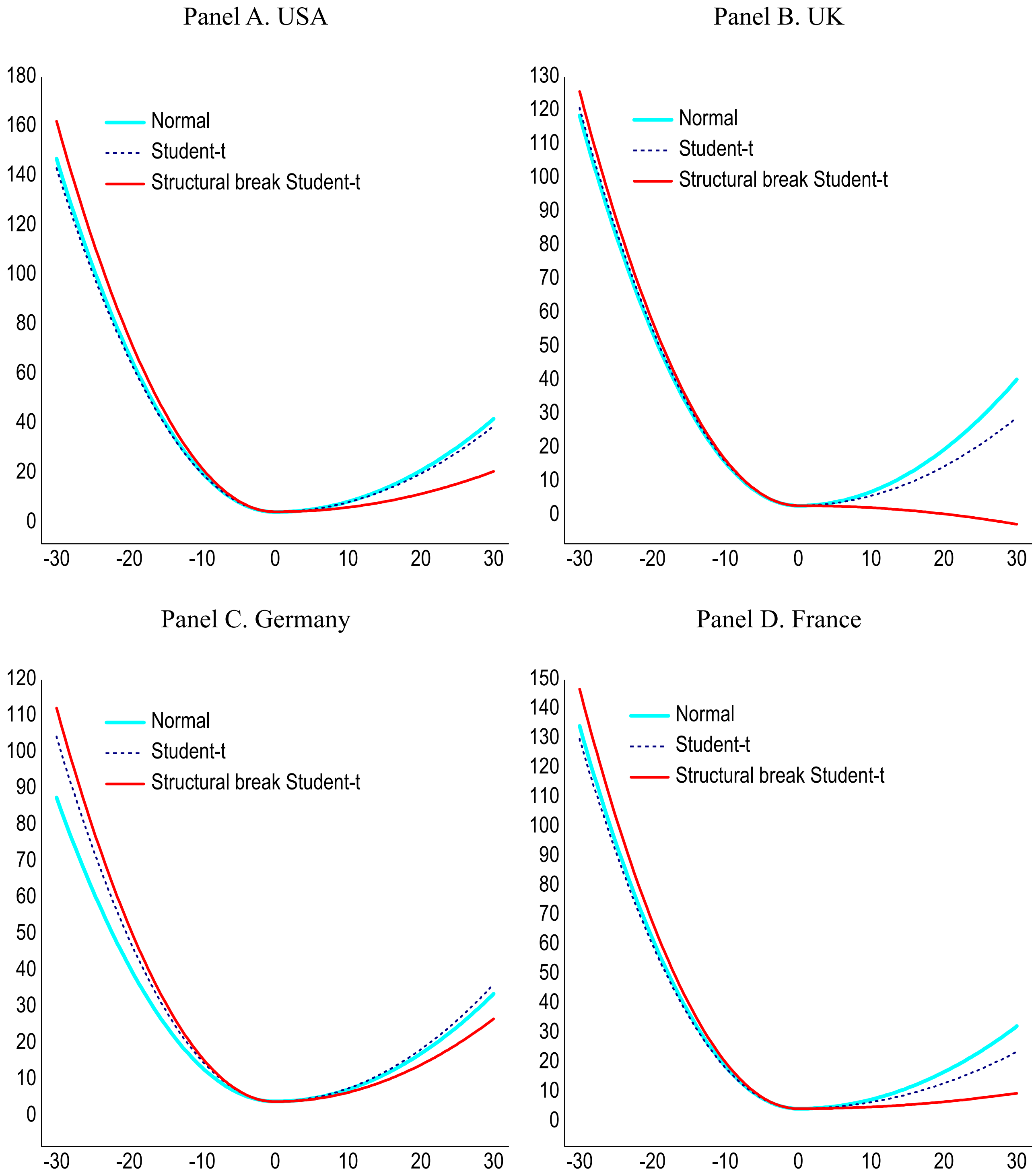


Figure 2. News impact curves of international banking stocks from the GJR models with or without structural breaks.

Note: The *x*-axis and *y*-axis show return residuals on day $t-1$ and variances on day t, respectively.

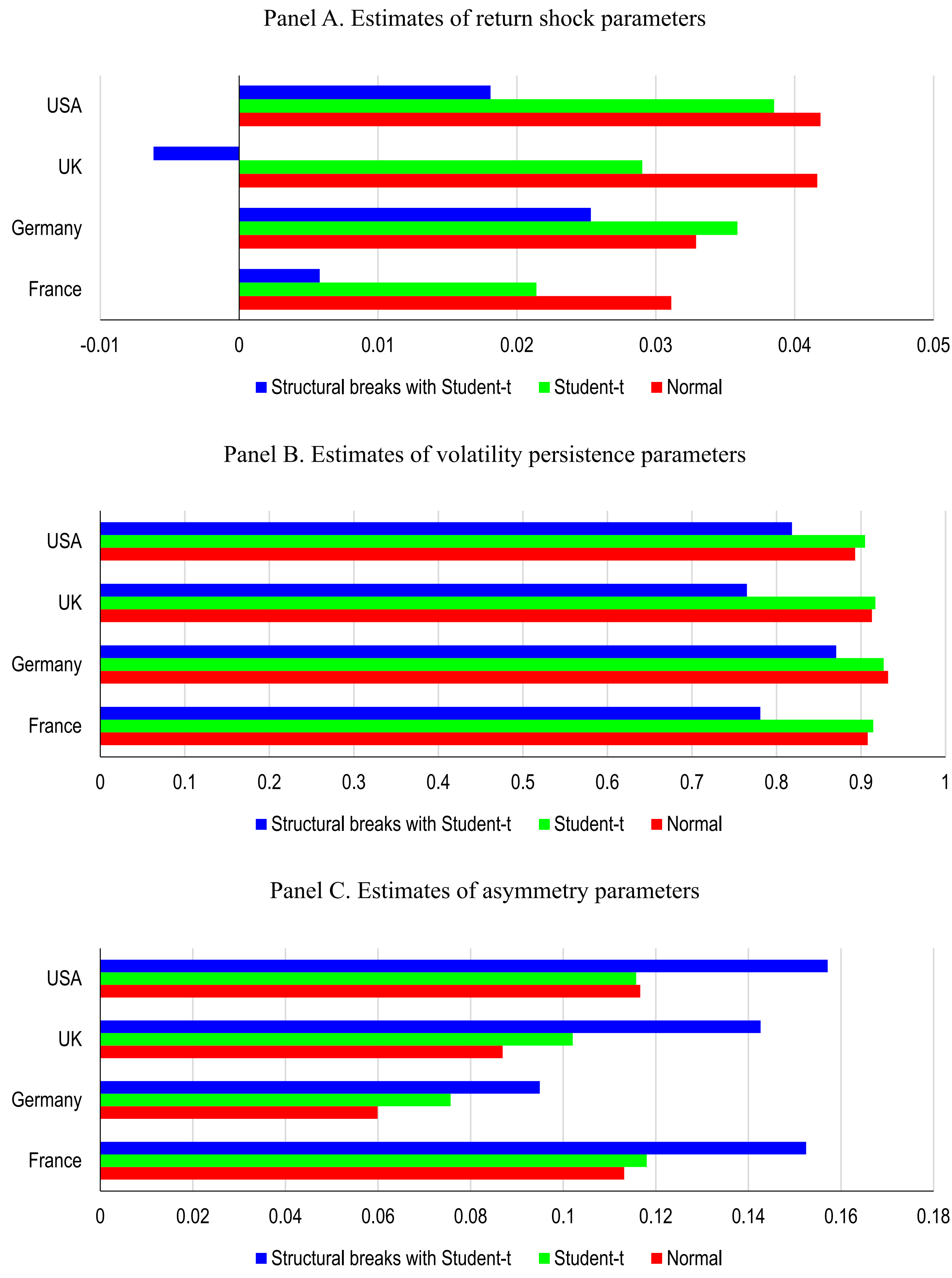


Figure 3. Parameter estimates of international banking stock volatilities from the GJR models with or without structural breaks.

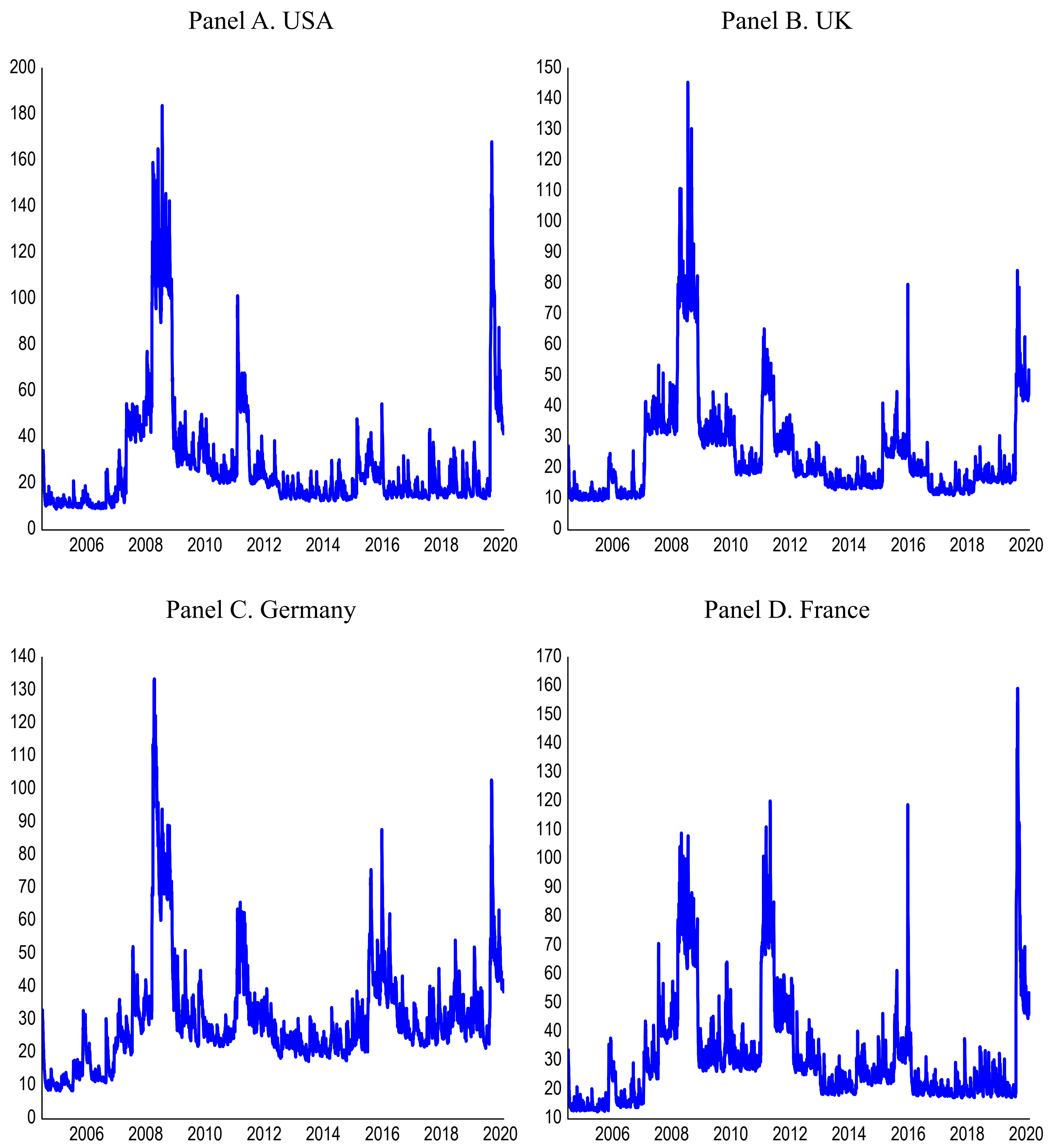


Figure 4. Time-series evolution of the estimated volatilities of international banking stock returns.

Note: All estimated volatilities are annualized and from the GJR models with structural breaks and Student-*t* errors.

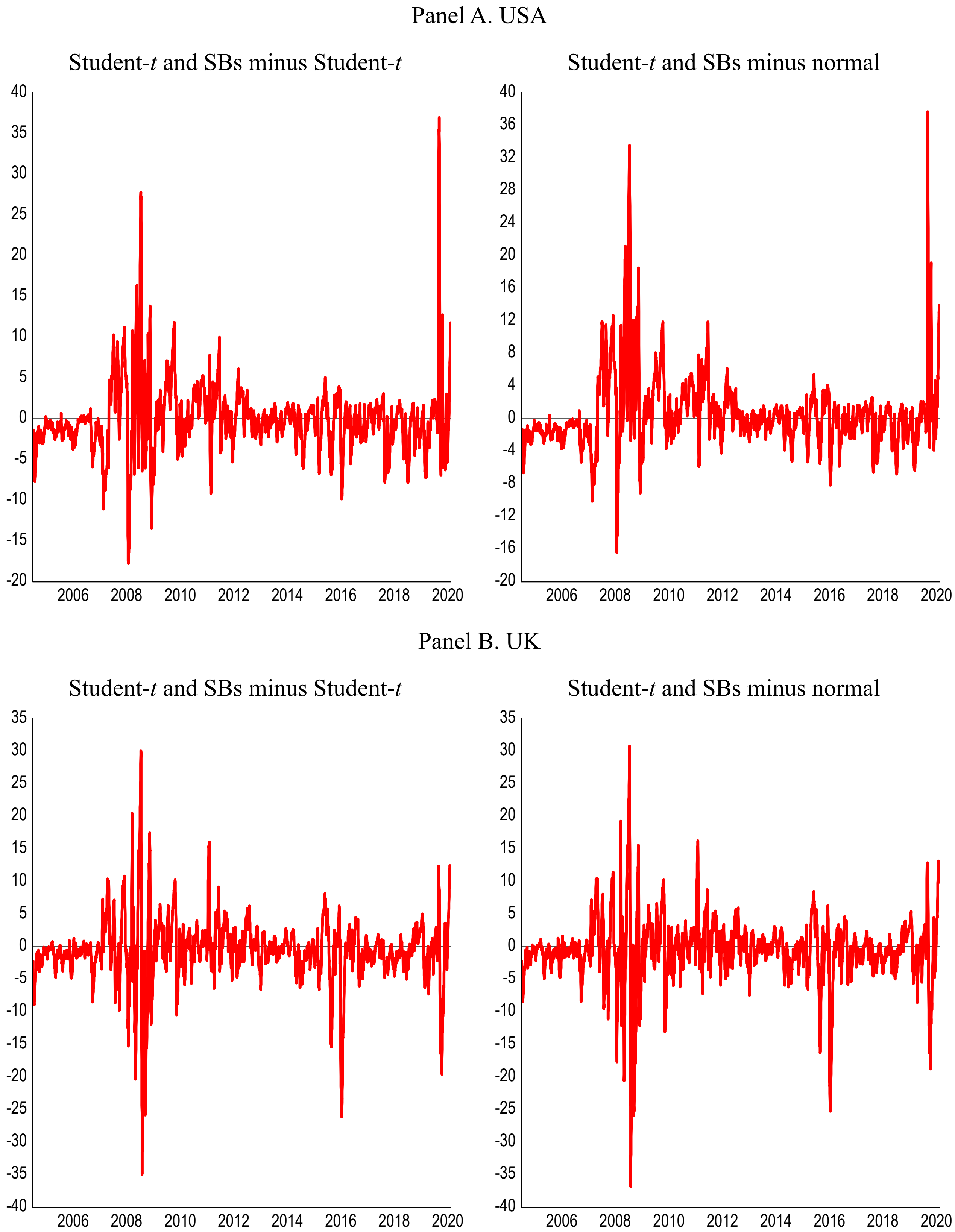
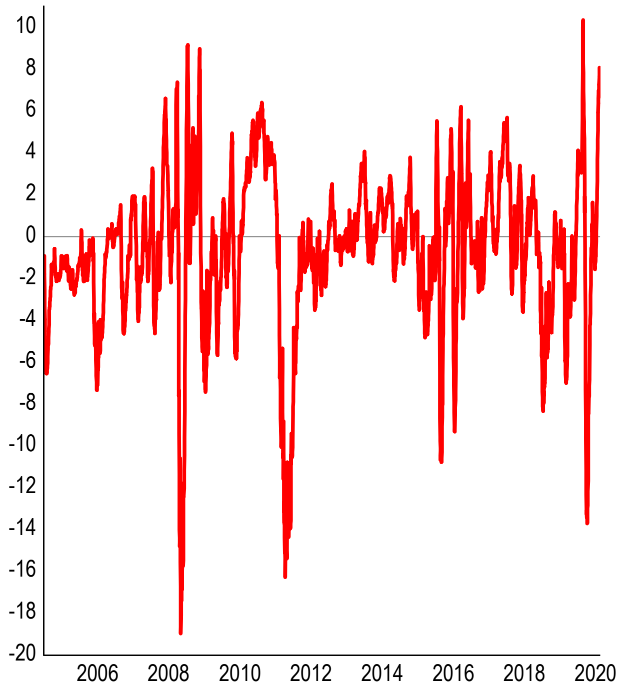


Figure 5. Evolution of the estimated volatility spreads of international banking stocks.

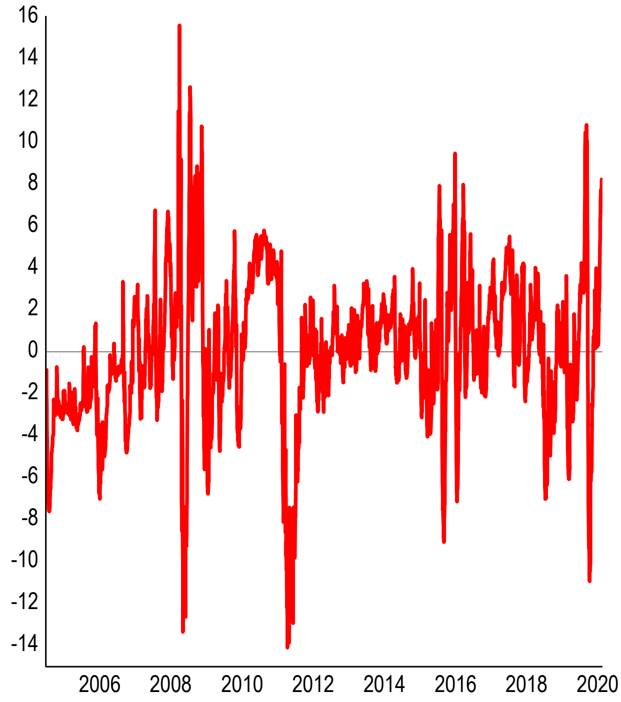
Note: SBs—structural breaks. All estimated volatility spreads are annualized and derived by using Equation (8) or (9).

Panel C. Germany

Student-*t* and SBs minus Student-*t*

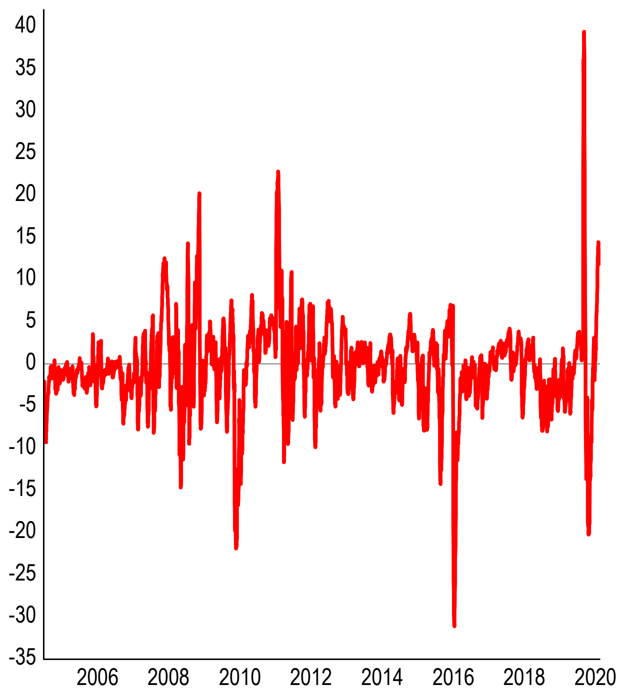


Student-*t* and SBs minus normal



Panel D. France

Student-*t* and SBs minus Student-*t*



Student-*t* and SBs minus normal

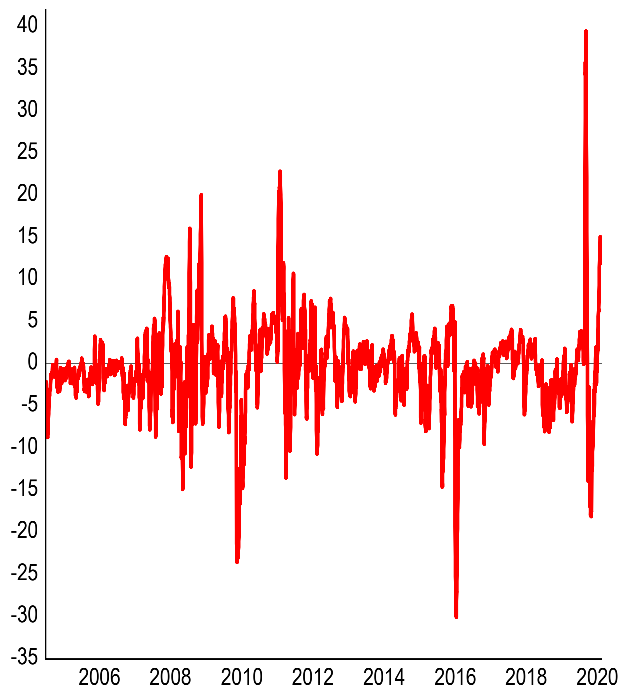


Figure 5. *Continued.*

6.3. What volatility estimates do structural breaks derive?

We next inspect the volatility estimates reflecting the structural breaks. Figure 4 plots the volatility estimates from our extended GJR with structural breaks and Student-t errors. Figure 4 shows the following unmistakable evidence. First, all the panels in Figure 4 show that the estimated volatilities jump in all the four countries during the Lehman crisis. Second, as all the panels show, the estimated volatilities increase in all the four countries during the European debt crisis. Third, as Panels B−D indicate, the estimated volatilities rise in all the countries except for the USA at the time of Brexit. Fourth, all the panels illustrate that the estimated volatilities jump in all the four countries at the time of the COVID-19 crisis.

As above, Figure 4 clearly demonstrates that incorporating Student-t errors and structural breaks enables us to capture the increases in volatilities more precisely at the time of risky events upsetting stock markets. We consider that as a result, the GJR models incorporating structural breaks more accurately capture the downside risk, as presented in Tables 5−8. In other words, these results newly signify that if we ignore tail fatness and structural breaks in volatility estimations, the estimated volatilities will undervalue the levels of downside risk when stock prices of international banking sectors plunge.

6.4. What volatility spreads do structural breaks derive?

To further deepen our understanding of the effects and meaning of structural breaks, we compare the importance of incorporating tail fatness (Student-t errors) and structural breaks in volatility estimations for capturing downside risk more effectively. For this purpose, we furthermore inspect the following two annualized volatility spreads:

$$\Delta\sigma_t^{Student\text{-}t\_SB-Student\text{-}t} = \sigma_t^{Student\text{-}t\_SB} - \sigma_t^{Student\text{-}t}, \tag{8}$$

$$\Delta\sigma_t^{Student\text{-}t\_SB-normal} = \sigma_t^{Student\text{-}t\_SB} - \sigma_t^{normal}. \tag{9}$$

The computational details of the two annualized volatility spreads are as follows. $\Delta\sigma_t^{Student\text{-}t\_SB-Student\text{-}t}$: annualized estimated volatilities from our extended GJR model with Student-t errors and structural breaks minus those from the same model with Student-t errors but without structural breaks; and $\Delta\sigma_t^{Student\text{-}t\_SB-normal}$: annualized estimated volatilities from our extended GJR model with Student-t errors and structural breaks minus those from the same model with normal distribution errors but without structural breaks.

Figure 5 plots the volatility spreads from our GJR models. In each panel, the left side shows $\Delta\sigma_t^{Student\text{-}t\_SB-Student\text{-}t}$, while the right side shows $\Delta\sigma_t^{Student\text{-}t\_SB-normal}$. Focusing on the clear evidence, Figure 5 shows that the estimated volatility spreads increase in all the four countries during the Lehman crisis and in the USA, Germany, and France during the COVID-19 crisis. We note that in Figure 5, the left side in all the panels presents the volatility spreads that reflect only the effect of the structural breaks, while the right side exhibits the volatility spreads that reflect the effects of both structural breaks and Student-t errors against normal distribution errors. However, in all the panels, the volatility spread evolution in the left- and right-side figures is all much the same, meaning that the volatility spread increases during the Lehman crisis in the four countries and during the COVID-19 crisis in the USA, Germany, and France should be solely because of the structural break effect.

As mentioned above, the clear evidence we derive from Figure 5 much strongly shows the importance of structural breaks and signifies that incorporating structural breaks evaluates the volatility increases to be higher in the Lehman and COVID-19 crisis period, although in some countries, the volatility spreads also increase during the European debt crisis or Brexit. Therefore, we consider that through these mechanisms, our extended GJR models with structural breaks much more accurately capture the downside risk, as presented in Tables 5−8. In other words, these results newly evidence that in volatility estimations to capture the downside risk in international banking sectors more effectually, incorporating structural breaks is more important than incorporating heavy-tailed densities.

7. Interpretation, implications, and innovative views for the post-COVID-19 era

This section discusses how we can interpret our results and derives significant broader implications and innovative views for risk management in the post-COVID-19 era. First, as presented in Tables 5−8, our results from probit and logit models robustly indicate that the estimated volatilities from our extended GJR models incorporating structural breaks more strongly capture the downside risk in international banking sector stocks, as measured by not only VaR but also ES. This means that if we do not take structural breaks into account, we will undervalue the volatility levels in plunging banking stock prices, leading to underestimating the downside risk. Therefore, in the post-COVID-19 era, we should pay much more keen attention to the significant stock volatility amplifications, particularly when large shocks cause structural breaks in stock markets.

Second, as shown in Figure 2, the computed NICs from our extended GJR models with Student-*t* errors and structural breaks more accurately capture the asymmetry in volatility responses to return shocks in banking sector stocks. We consider that the NICs from our best GJR model—incorporating Student-*t* errors and structural breaks, which was identified by the LR tests in Table 3—are most accurate. Moreover, as presented in Figure 3, when incorporating structural breaks, the estimated asymmetry parameters all clearly increase in the GJR models, also showing that our extended models incorporating structural breaks evaluate volatility asymmetry much more strongly than in models without structural breaks. This means that if we ignore structural breaks, we will underestimate the asymmetric feature of volatilities; hence, it is vital for us to be more cautious about the larger actual volatility asymmetry in our risk management in the post-COVID-19 era. We further emphasize that the behavioral science theory of loss aversion (Benartzi and Thaler, 1995) which advocates that people are more sensitive to losses than gains, is consistent with the asymmetric feature of volatilities. Also from this theoretical viewpoint, our results for volatility asymmetry and their interpretation are critically important for risk management in the more unforeseen post-COVID-19 world.

Third, as shown in Figure 5, the computed volatility spreads between the volatilities from our extended GJR models with structural breaks and those from the corresponding models without structural breaks rise during the Lehman crisis in all the four countries and during the COVID-19 crisis in the USA, Germany, and France. In addition, in Figure 1, we can see that during the Lehman crisis, some successive structural breaks are much clearly identifiable in all the four countries. These results clearly prove the importance to be much cautious about some successive structural breaks in sudden and worldwide negative economic events like the Lehman crisis. Therefore, for proper risk management in the more unpredictable post-COVID-19 world, we should be particularly cautious regarding some significant successive structural breaks in stock returns.

Fourth, as presented in Table 4, when incorporating structural breaks, all the DOF parameter values of Student-*t* densities became higher, also proving the importance of structural breaks because this means that structural breaks partly explain all the banking sector stock return fat tails. Our uncovering of this structural break effect is highly crucial from the viewpoint of engineering. Hence, as a significant technical implication, we stress that it is important to incorporate not only fat-tailed densities but also structural breaks into quantitative models simultaneously for proper model estimations and conducting more appropriate risk management in the more uncertain post-COVID-19 era.

Fifth, as shown in Figure 2, when incorporating structural breaks, all the NICs of the four countries exhibit their weakest volatility responses to positive return shocks, and we stress that these responses were quite small in magnitude. Ross (1989) theoretically argued that the volatility amplification reflects an increase in the information for the asset. Considering this, we can derive a significant interesting implication from the viewpoint of information. That is, it is negative information in the form of sudden and large negative return shocks that causes structural breaks and much larger volatility amplifications. Hence, we should more strongly recognize that only negative information that can be measured by sudden and large negative return shocks and causes serious structural breaks is important for risk management in the more unpredictable post-COVID-19 world.

Sixth, from the perspective of payout policy for dividend distributions and share buybacks, we derive another significant implication. That is, we consider that in preparation for sudden and worldwide negative events that cause structural breaks, international banks should keep ample shareholder equity to endure sudden structural breaks and subsequent recessions on a routine basis given sufficient equity is especially critical for all banks. We thus emphasize that in the more uncertain post-COVID-19 era, it is the best form of risk management not only for banking industries but also for all the other industries to maintain their capital buffer much more carefully while pondering deeply about their payout policies in ordinary times preparing especially for sudden structural breaks caused by various negative events.

Based on the above discussion, we further derive several innovative views for risk management in the post-COVID-19 era. As reviewed in Zhu et al. (2021), artificial intelligence (AI) should play a significant role in future risk management. Our innovative views are as follows. First, as demonstrated, volatilities should be estimated by incorporating both fat-tailed densities and structural breaks. Therefore, it is highly beneficial for us to forecast these volatilities precisely by applying innovative AI techniques of machine learning for more effective risk management in the post-COVID-19 era.

Second, accurate recognition of the volatility asymmetries is crucial for risk management. Thus, it is also highly significant for us to forecast NIC curves precisely by applying innovative AI technologies for more effectual risk management in the more unpredictable post-COVID-19 era. Third, paying keen attention to some successive structural breaks is vital in risk management. Hence, it is particularly important for us to accurately forecast structural breaks by applying innovative AI technologies for more effective risk management in the more unforeseen post-COVID-19 world. We also consider that if we could accurately forecast structural breaks by AI techniques, we might be able to conduct effective out-of-sample tests by using those structural break forecasts.

Fourth, negative return shocks are important for risk management. Therefore, it is also highly significant for us to forecast the direction and magnitude of asset price movement by applying such innovative AI techniques as machine learning and to use the forecast results to conduct more proper risk management in the post-COVID-19 era. Finally, for all firms, more cautious and thoughtful payout policies are vital for future risk management. Hence, the collaborations of AI and corporate executives such as chief financial officers are crucially important for more appropriate risk management in the more uncertain post-COVID-19 world.

The thorough inspections undertaken in this paper provide numerous meaningful interpretations and implications along with several significant innovative viewpoints. We consider that these all show how our findings matter for risk management, and also importantly, how our significant interpretations, implications, and innovative views provide an additional crucial and valuable contribution through this study.

8. Contributions and conclusions

This study investigated the meaning of structural breaks in risk management in the banking sectors of the USA, the UK, Germany, and France. As a result of our rigorous quantitative analysis, we derived the following significant contributions. First, the LR tests for our extended GJR models robustly signified that when estimating all four banking stock volatilities, incorporating structural breaks is always effective, and this shows our worthwhile contribution. Second, our extended GJR estimations evidenced that structural breaks also explain partially the tail fatness of international banking sector stock returns. This means that to incorporate not only Student-*t* densities but also structural breaks into GARCH models simultaneously is highly meaningful when modeling international banking stock volatilities. We consider that this new evidence also demonstrates our contribution and should also be interesting from an engineering viewpoint.

Third, our results from both probit and logit models robustly showed that when including structural breaks, the estimated volatilities from our extended GJR models more accurately capture the downside risk in international banking stocks, which is measured by not only VaR but also ES. This signifies that if we ignore structural breaks, we will undervalue the volatilities when international banking stock prices plunge; thus, this new evidence is also a significant contribution showing how structural breaks are crucial for downside risk management. Fourth, we also found that when incorporating structural breaks, the computed NICs from our extended GJR models more strongly capture the asymmetry in international banking stock volatility responses to their return shocks. This showed why the estimated volatilities from our extended models with structural breaks more strongly explain the downside risk; and hence this new finding also shows the significant contribution of this study.

Fifth, we also showed that when incorporating structural breaks, the estimated asymmetry parameters in our extended GJR models evaluate volatility asymmetry to be much larger. This also explains why structural breaks matter in volatility estimations to capture the downside risk more accurately; and thus this new evidence also presents the important contribution of our work. Sixth, we further found that the estimated volatilities from our extended GJR models with structural breaks sharply increase at the time of highly momentous events such as the Lehman crisis, the European debt crisis, Brexit, and the recent COVID-19 crisis. This also shows why the estimated volatilities from our extended models with structural breaks more precisely capture the downside risk, also demonstrating our significant contribution.

Seventh, we furthermore showed that our computed volatility spreads between the volatilities from our extended GJR models with structural breaks and those from the corresponding models without structural breaks rise during the Lehman and COVID-19 crises, when international banking stock prices especially plunged, and their volatilities especially rose. This is the newly found mechanism that explains why including structural breaks is so effective in capturing the downside risk very strongly; and therefore this clarification also shows the novelty of this study. Eighth, in addition to the abovementioned points, we further derived and presented many broad and beneficial interpretations, implications, and innovative views for risk management in the post-COVID-19 era; and this is yet another novel contribution of our work. These interpretations, implications, and innovative views should be highly meaningful for not only academic researchers but also industry practitioners.

We note that although not reported for brevity, we also analyzed by using similarly extended EGARCH models, and all the results were much the same. Therefore, our all results presented in this paper are highly robust. We stress that in contrast to existing studies, our present work has uncovered not only how but also why structural breaks matter for downside risk management. We therefore trust that the new evidence alongside the significant and beneficial interpretations, implications, and innovative views for risk management in the post-COVID-19 world derived from this study amply contributes to not only past studies but also future innovative research in many related fields.

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Conflict of interest

The author declares no conflicts of interest in this paper.

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