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Banks' Contribution and Exposure to Systemic Risk amid Natural Disasters: Evidence from Malaysia

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Abstract: This study evaluates the extent to which banks in Malaysia have contributed to and been impacted by systemic risk in the wake of natural disaster events during a period spanning from 1 January 2007 to 31 March 2022. Employing delta conditional value-at-risk (Δ*CoVaR*) measures, our findings reveal that natural disasters, akin to past crises such as the global financial crisis and the COVID-19 pandemic, elevate systemic risk in the banking sector, though the magnitude of their impact is relatively less severe. Additionally, we find that there were more instances, either during the natural disaster event or in its aftermath, where the banks increased their contribution to systemic risk compared to instances where they experienced heightened systemic risk exposure. In terms of timing of the reaction, our analysis shows that the market exhibits a notable delay, with both systemic risk contribution and exposure primarily increasing after the disaster event has concluded, rather than during its occurrence. These results underscore the critical need for climate resilience in the banking industry and provide important insights into the systemic risk implications of natural disasters, particularly in developing, bank-centric countries like Malaysia. They also inform the formulation of targeted policy measures to effectively mitigate these risks.

Keywords: Conditional value-at-risk, banks, Malaysia, natural disaster, systemic risk
JEL classification: G21, Q51, Q54

1. Introduction

Understanding and managing the impacts of natural disasters on the banking industry by market regulators is of paramount importance as climate change intensifies, leading to greater frequency and severity of extreme weather events. In Malaysia, the central bank, Bank Negara Malaysia (BNM), has designed a comprehensive strategic plan to fortify the climate resilience of the banking sector in the country. BNM's multifaceted initiatives include the provision of a climate change and principle-based taxonomy, which helps banks classifying economic activities based on their environmental impact, guidelines on stress testing and scenario analysis for climate-related risks, rigorous disclosure requirements to bolster climate transparency, green and social capacity building, as well as a dynamic regulatory framework that aligns harmoniously with international best practices.[1] In doing so, BNM continues to engage with various

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[1] BNM has diligently undertaken regulatory and supervisory policies addressing climate-related risks, notably since 2019. For more details about these initiatives, please visit https://www.bnm.gov.my/climatechange

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stakeholders, while placing a pivotal emphasis on research and data utilisation to effectively assess and manage climate-related risks. These concerted efforts are aimed at positioning Malaysia's banking sector to navigate the challenges of climate change, enhance its sustainability, and contribute to a global shift toward climate-resilient financial systems.

In tandem with these endeavours, this study intends to add to the burgeoning body of literature elucidating the ramifications of natural disasters on banks' solvency. Previous studies have looked at how these calamities can push banks towards distress, predominantly through the lenses of profitability and capital adequacy (Apergis & Apergis, 2022; Brei et al., 2019; Do et al., 2023; Financial Stability Board, 2020; Klomp, 2014; Walker et al., 2023). While it is evident that the interconnectedness among financial intermediaries can significantly exacerbate the effects of natural disasters (Battiston et al., 2017; Battiston et al., 2021; DeMenno, 2023), there remains a dearth of attempts addressing this issue from a systemic risk perspective. Correspondingly, the incorporation of climate change as an emerging source of systemic risk has not gained widespread attention in the banking systemic risk literature. A notable exception is the study of Curcio et al. (2023) investigating the response of systemic risk in the US banking and insurance sectors to climate-related catastrophes occurring between December 2015 and July 2022. Their findings demonstrate that certain extreme events can amplify financial systemic risk, shedding light on the varying timing of systemic risk measure responses. In a comparable vein, Wu et al. (2023) suggested that changes in climatic conditions could potentially elevate the extent of systemic risk spillovers among Chinese commercial banks. In other relevant studies, researchers have focused on temperature shocks and have established a positive association with bank systemic risk (Liu et al., 2020; Song & Fang, 2023).

Our approach exhibits parallels to the work of Curcio et al. (2023), albeit marked by at least three distinctions. First, we provide lessons from a developing country, Malaysia, whose financial system is highly dependent on banks. In contrast to the US banking market, characterised by a multitude of small banks primarily operating within specific counties, most Malaysian banks maintain a nationwide presence, with branches and other facilities extending across nearly all states, particularly in regions prone to natural disasters, especially floods. The growing intensity and frequency of climate-related disasters in Malaysia over the past decades have posed a significant threat to the banking sector's ability to sustain its operations and thus effectively support the broader economy. Between 1998 and 2018, Malaysia incurred a total damage of about RM8 billion, approximately equivalent to the construction cost of its national landmark, the Petronas Twin Towers, due to climate disaster events, affecting more than three million people through displacements, injuries and deaths. It is estimated that approximately 11.7% of the country's banking assets are directly exposed to climate change. BNM has raised a further concern that, "if not dealt with adequately, climate change can also pose a systemic risk" (BNM, 2020, p. 20). In this paper, using a market-based systemic risk measure, namely the delta conditional value-at-risk ($\Delta CoVaR$) developed by Adrian and Brunnermeier (2016) and natural disasters data between the period 1 January 2007 and 31 March 2022, we provide evidence that such concern prompting the Malaysian central bank's urgent efforts to promote the banking sector's climate resilience has a basis. Second, our analysis encompasses not only the markets' reaction to natural disasters in terms of banks' contributions to systemic risk but also their susceptibility to systemic risk. We find that the banks' systemic risk contribution experiences a slightly more pronounced increase in comparison to their exposure during and after the termination of natural disaster events. Lastly, our analysis period extends over a more substantial duration, from 1 January 2007 to 31 March 2022, allowing us to compare the systemic risk responses to natural disasters with those of other crises, including the global financial crisis (GFC) of 2007−2009, the oil price plunge of 2014−2016, and the COVID-19 pandemic. We show that the average increase in the systemic risk responses to natural disasters is smaller in magnitude as compared to those observed for the GFC and COVID-19 periods.

The remainder of this paper is structured as follows. Sections 2 and 3 describe research methods and data, respectively. Section 4 discusses the results. Lastly, Section 5 concludes and provides policy recommendations.

2. Methodology

2.1 Constructing the Systemic Risk Measures

We begin by estimating the levels of systemic risk contribution and exposure of Malaysian banks measured by the $\Delta CoVaR$. Systemic risk contribution evaluates the extent to which an individual bank adds to the overall systemic risk of the financial system, emphasising the potential threat the bank poses to the system's stability. Conversely, systemic risk exposure quantifies the degree to which a particular bank is susceptible to systemic risk originating from the entire financial system, indicating the risk that external systemic events pose to the bank.

The $\Delta CoVaR$ was introduced by Adrian and Brunnermeier (2016) as a measure for market-based systemic risk building upon the widely used measure of risk used by financial institutions, namely the value-at-risk (*VaR*). While the *VaR* calculates the risk of an individual bank in isolation, it falls short in capturing the bank's contribution to the overall risk of the financial system, making regulation insufficient to curb excessive risk-taking. Aimed at overcoming this limitation, the $\Delta CoVaR$ captures the conditional tail-dependency (i.e., risk spillovers) between the bank and the whole banking system in a non-causal sense. The procedures for constructing the $\Delta CoVaR$ estimates are explained below.

Recall that VaR_q^i is typically a negative number[2] defined as the percentage of asset value (R^i) that bank *i* might lose with the *q*% confidence level:

$$\Pr(R^i \leq VaR_q^i) = q \tag{1}$$

Let $CoVaR_q^{s|i}$ represents the *VaR* of the entire banking system conditional on the loss of bank *i* is at its level of *VaR* (i.e., $R^i = VaR_q^i$). As such, $CoVaR_q^{s|i}$ can be expressed by the *q*% quantile of the following conditional probability distribution:

[2] Consistent with Adrian and Brunnermeier (2016) and other previous studies, we, however, reverse the sign for easy interpretation.

$$\Pr(R^{s} \leq CoVaR_{q}^{s|i} \mid R^{i} = VaR_{q}^{i}) = q \tag{2}$$

The $CoVaR_{q,t}^{s|i}$, or bank *i*'s marginal contribution to systemic risk, is now defined as the difference between the banking system's *VaR* conditional on bank *i* being in distress and the banking system's *VaR* conditional on bank *i* operating in its median state:

$$\Delta CoVaR_{q,t}^{s|i} = CoVaR_{q,t}^{s|R^{i}=VaR_{q}^{i}} - CoVaR_{q,t}^{s|R^{i}=VaR_{median}^{i}} \tag{3}$$

Following the approach of Adrian and Brunnermeier (2016), we rely on quantile framework (Koenker & Bassett, 1978) to estimate the $\Delta CoVaR_{q}^{s|i}$. As done by Brunnermeier et al. (2020), we run the following quantile regressions at the 1% and 50% quantiles using daily data:

$$R_{t}^{i} = \alpha_{q}^{i} + \beta_{q}^{i} Z_{t-1} + \varepsilon_{q,t}^{i} \tag{4}$$

$$R_{t}^{s} = \alpha_{q}^{s|i} + \beta_{q}^{s|i} Z_{t-1} + \gamma_{q}^{s|i} R_{t-1}^{i} + \varepsilon_{q,t}^{s|i} \tag{5}$$

where α_{q}^{i} and $\alpha_{q}^{s|i}$ represent the constants. $\varepsilon_{q,t}^{i}$ and $\varepsilon_{q,t}^{s|i}$ are the error terms. R_{t}^{i} is the daily growth rate of the market value (MV) of bank *i*'s equity at time *t* (i.e., $R_{t}^{i} = \frac{MV_{t}^{i}}{MV_{t-1}^{i}} - 1$). R_{t}^{s} is the daily growth rate of the market value of the equity of all banks in the system (*i*=*j*=1,2,…N) at *t*. Note that when calculating the R_{t}^{s} in Eq. (5), the individual bank's equity return has to be value-weighted by its market value (i.e., $R_{t}^{s} = \sum_{i=1}^{N} \frac{MV_{t-1}^{i} \times R_{t}^{i}}{\sum_{j=1}^{N} MV_{t-1}^{i}}$). Z_{t-1} is a vector of lagged state variables as done in Brunnermeier et al. (2020) and Morelli and Vioto (2020) for the US and Chinese markets, respectively, listed in Table 1. These variables capture time-variation in the joint distribution of system R^{i} and R^{s} that could influence the banks' systemic risk contribution.

Next, we compute an individual bank's predicted *VaR* for each quantile using the estimated coefficients α_{q}^{i} and β_{q}^{i} from Eq. (4):

$$VaR_{q,t}^{i} = \hat{\alpha}_{q}^{i} + \hat{\beta}_{q}^{i} Z_{t-1} \tag{6}$$

Likewise, we compute the predicted *CoVaR* of individual banks for each quantile using the estimated coefficients $\alpha_{q}^{s|i}$, $\beta_{q}^{s|i}$, and $\gamma_{q}^{s|i}$ from Eq. (5) and the estimates of $VaR_{q,t}^{i}$ from Eq. (6):

$$CoVaR_{q,t}^{s|i} = \hat{\alpha}_{q}^{s|i} + \hat{\beta}_{q}^{s|i} Z_{t-1} + \hat{\gamma}_{q}^{s|i} VaR_{q,t}^{i} \tag{7}$$

The $\Delta CoVaR_{q,t}^{s|i}$ is then calculated by subtracting the predicted *CoVaR* at the 1% quantile (i.e., in distress) from the one at the 50% quantile (i.e., in normal state) as specified in Eq. (3).

Similarly as done by Zhang et al. (2021), we then reverse the direction of the conditional probability distribution in Eq. (2) to focus on the systemic risk exposure of bank *i* to the following:

$$\Pr(R^{i} \leq CoVaR_{q}^{i|s} \mid R^{s} = VaR_{q}^{s}) = q \tag{8}$$

Table 1. Definitions and summary statistics of state variables

State variable	Definition	Justification	Mean	Std. Dev.	Min.	Max.	Kurtosis	Skewness	Obs.
Market return	FTSE Bursa Malaysia KLCI daily returns.	It provides a snapshot of market performance and investor sentiment, which can have significant implications for the risk profiles of the banks.	0.012	0.745	-9.497	6.851	15.601	-0.712	3,979
Volatility	22-day rolling standard deviation of the daily KLCI returns.	It captures historical risk fluctuations in bank share FTSE Bursa Malaysia prices.	0.651	0.356	0.167	2.775	11.245	2.362	3,979
Liquidity risk	Difference between the 3-month KLIBOR rate and the 3-month Malaysian Treasury bill rate.	It provides a direct measure of the ease of converting assets to cash. During periods of market turmoil, liquidity can dry up, resulting in fire sales of assets and further declines in asset prices.	31.066	15.491	-14.000	84.000	3.740	0.860	3,979
Interest-rate risk	Change in the 3-month Malaysian Treasury bill rate from t to $t-1$.	It indicates implications for the valuation of financial instruments, borrowing costs, and the overall financial stability of the banks.	-0.039	2.339	-47.500	57.500	269.866	-3.735	3,979
Term structure	Change in the difference between the 10-year Benchmark Malaysian Government Bond rate and the 3-month Malaysian Treasury bill rate.	It represents interest rate related risks across different maturities for a similar debt instrument.	0.042	3.968	-57.000	45.300	29.802	0.272	3,979

Table 1. Continued

State variable	Definition	Justification	Mean	Std. Dev.	Min.	Max.	Kurtosis	Skewness	Obs.
Credit risk	Change in the difference between the S&P Malaysia Corporate Bond Index and the 10-year Benchmark Malaysian Government Bond rate.	It directly measures the perceived risk of default by corporate borrowers, impacting their cost of borrowing.	-0.020	5.393	-102.100	105.000	98.228	-0.683	3,979
Real estate excess return	Difference between the Bursa Malaysia Real Estate Index returns and the Bursa Malaysia Finance Index returns.	It provides insights into the health of the real estate sector relative to the financial sector. The real estate sector is often linked to broader economic conditions. A downturn in real estate markets can lead to widespread financial instability, affecting other sectors and institutions.	-0.013	0.798	-6.586	6.106	10.793	-0.291	3,979

Note: This table presents the definitions and summary statistics for the state variables used in the quantile regressions for estimating Eq. (5). All data are extracted from Thomson Reuters Datastream for the period from 1 January 2007 to 31 March 2022.

Thus, bank *i*’s systemic risk exposure can be defined as the difference between the bank’s *VaR* conditional on the banking system being in distress and the bank’s *VaR* conditional on the banking system operating in its median state:

$$\Delta CoVaR_{q,t}^{i|s} = CoVaR_{q,t}^{i|R^s=VaR_q^s} - CoVaR_{q,t}^{i|R^s=VaR_{median}^s} \tag{9}$$

To provide context for benchmarking these estimates, it is essential to compare the $\Delta CoVaR$ values across different banks. Banks with higher $\Delta CoVaR^{s|i}$ values are more systemically important, meaning their distress could have more severe implications for the overall financial system. Similarly, banks with higher $\Delta CoVaR^{i|s}$ values are more exposed to systemic risk, meaning they are more likely to be affected by the distress in the broader financial system.

2.2 Testing Bank Systemic Risk Response to Natural Disasters

Additionally, using the $\Delta CoVaR$ estimates computed, we perform tests to investigate the response of these market-based systemic risk measures to the information deriving from a series of natural disaster events observed in the country. Like in Morelli and Vioto (2020) and Curcio et al. (2023), we use the Wilcoxon signed rank sum test for paired data.[3] We chose the non-parametric Wilcoxon test due to its relaxation of the assumption of normality. In the context of the present study, climate events may often violate the normal distribution assumption for several reasons. First, climate events, such as floods and droughts, can result in severe financial losses for banks, leading to outliers in the data. These extreme values would skew the distribution of risk measures like *VaR* and $\Delta CoVaR$, resulting in a distribution that deviates significantly from normality. Climate events can also cluster in time, causing periods of high volatility followed by relatively calm periods, which leads to a distribution with heavy tails rather than a bell-shaped curve. Furthermore, sudden shifts in the financial environment due to climate events, such as regulatory changes or abrupt changes in market sentiment and bank operations, can result in regime changes that contribute to a non-normal distribution. In addition, we run the Welch’s *t*-test as a robustness check. The Welch’s *t*-test is a parametric test that can accommodate unequal variances between groups. It is particularly useful when the normal distribution assumptions are reasonably met. The results of the Welch’s *t*-test are provided in Appendix 1. Performing both tests allows for a sensitivity analysis of the results. If the results are consistent across both tests, it suggests that the conclusions are reliable regardless of different assumptions about the data distribution.

We first test whether the systemic risk contribution ($\Delta CoVaR^{i|s}$) and exposure ($\Delta CoVaR^{s|i}$) of Malaysian banks during the h days a natural disaster lasts (i.e., between day t and day $t+h$) is greater than those observed h days before. To do so, the Wilcoxon signed rank sum test is applied to the following null hypotheses:

$$H_0 : \Delta CoVar_{t:t+h}^{s|i} \leq \Delta CoVar_{t-h-1:t-1}^{s|i} ; \Delta CoVar_{t:t+h}^{i|s} \leq \Delta CoVar_{t-h-1:t-1}^{i|s} \tag{10}$$

[3] For a more detailed explanation of the Wilcoxon signed rank sum test, please see Wilcoxon (1947).

$$H_1 : \Delta CoVar_{t:t+h}^{s|i} > \Delta CoVar_{t-h-1:t-1}^{s|i} ; \Delta CoVar_{t:t+h}^{i|s} > \Delta CoVar_{t-h-1:t-1}^{i|s} \quad (11)$$

where i and s refers to the bank and banking system analysed, respectively, t is the day when the natural disaster starts, and h are the days the natural disaster lasts. The failure to reject the null hypotheses in (10) suggests that the market does not perceive an increase in systemic risk contribution (exposure) level of the sample banks during a specific natural disaster event.

Next, we test whether the systemic risk contribution and exposure of the Malaysian banks during the h days after the natural disaster event ends (i.e., from day $t+h+1$ to day $t+2h+1$) is greater than those recorded for the h days prior to the first day of the event (i.e., from day $t-h-1$ to day $t-1$) by applying the Wilcoxon signed rank sum test to another two null hypotheses as follows:

$$H_0 : \Delta CoVar_{t+h+1:t+2h+1}^{s|i} \leq \Delta CoVar_{t-h-1:t-1}^{s|i} ; H_0 : \Delta CoVar_{t+h+1:t+2h+1}^{i|s} \leq \Delta CoVar_{t-h-1:t-1}^{i|s} \quad (12)$$

$$H_1 : \Delta CoVar_{t+h+1:t+2h+1}^{s|i} > \Delta CoVar_{t-h-1:t-1}^{s|i} ; H_1 : \Delta CoVar_{t+h+1:t+2h+1}^{i|s} > \Delta CoVar_{t-h-1:t-1}^{i|s} \quad (13)$$

The failure to reject the null hypotheses in (12) suggests that the level of systemic risk contribution (exposure) of the sample banks in the post-disaster period is not perceived by the market to be higher than it was in the pre-disaster period.

Finally, we apply the Wilcoxon signed rank sum test to investigate whether the systemic risk contribution and exposure of the Malaysian banks during the h days after the last day of the natural disaster event (i.e., from day $t+h+1$ to day $t+2h+1$) is greater than those experienced by the banks during the event (i.e., from day t to day $t+h$) with the following null hypotheses to be tested:

$$H_0 : \Delta CoVar_{t+h+1:t+2h+1}^{s|i} \leq \Delta CoVar_{t:t+h}^{s|i} ; H_0 : \Delta CoVar_{t+h+1:t+2h+1}^{i|s} \leq \Delta CoVar_{t:t+h}^{i|s} \quad (14)$$

$$H_1 : \Delta CoVar_{t+h+1:t+2h+1}^{s|i} > \Delta CoVar_{t:t+h}^{s|i} ; H_1 : \Delta CoVar_{t+h+1:t+2h+1}^{i|s} > \Delta CoVar_{t:t+h}^{i|s} \quad (15)$$

The failure to reject the null hypotheses in (14) suggests that the market does not perceive that the sample banks' post-disaster level of contribution (exposure) to systemic risk exceeds their contribution (exposure) level during the disaster.

3. Data

Our analysis is performed on a sample of all ten Malaysian banks continuously listed during the sample period from 1 January 2007 to 31 March 2022. Our data thus contain 3,978 daily observations for each bank. Table 2 describes their daily equity returns and other information, such as market capitalisation and shares. The period covers major risk events such as the GFC, the oil price crash, and the COVID-19 pandemic. The GFC period spans from 2 August 2007 to 31 March 2009 as defined by several regulators (e.g., Bank for International Settlements, 2009; Federal Reserve Bank of St. Louis, 2010). The oil price crash period spans from 25 July 2014 to 11 February 2016 as defined by previous similar studies (e.g., Pham et al., 2021; Wang, 2021). The COVID-19 pandemic period spans from 27 January 2020 (i.e., the first trading day after

Table 2. List of sample banks and summary statistics of their daily equity returns

Bank	Acronym	Listed date	Market capitalisation (billion RM)	Shares (%)	Mean	Std. dev.	Min.	Max.	Kurtosis	Skewness	Obs.
Affin Bank Berhad	AFF	04/11/1991	4.25	1.20	0.027	1.601	-11.628	23.536	28.328	1.943	3,979
Alliance Bank Malaysia Berhad	ALL	02/01/1986	5.82	1.65	0.032	1.607	-10.695	17.170	10.870	0.169	3,979
AMMB Holdings Berhad	AMMB	01/12/1988	12.30	3.49	0.028	1.587	-12.717	20.747	17.654	0.625	3,979
BIMB Holdings Berhad	BIMB	17/01/1992	6.36	1.80	0.079	2.162	-25.148	40.243	71.676	3.787	3,979
CIMB Group Holdings Berhad	CIMB	03/11/1987	54.48	15.44	0.033	1.591	-13.726	15.924	12.592	0.329	3,979
Hong Leong Bank Berhad	HLB	17/10/1994	43.79	12.41	0.047	1.164	-9.029	11.811	17.612	1.132	3,979
Malaysia Building Society Berhad	MBSB	14/03/1972	4.30	1.22	0.096	2.881	-14.287	88.085	247.898	9.306	3,979
Malayan Banking Berhad	MYB	19/03/1984	106.19	30.10	0.030	1.303	-7.487	36.313	158.290	5.382	3,979
Public Bank Berhad	PUB	19/03/1984	90.65	25.69	0.036	1.023	-7.254	12.418	25.511	1.226	3,979
RHB Bank Berhad	RHB	02/01/1986	24.69	7.00	0.049	1.703	-23.934	36.043	74.016	2.780	3,979

Notes: This table provides a list of all banks in the sample and reports the summary statistics of their daily equity returns. The market capitalisation is as of 31 March 2022. Shares are calculated as the ratios of a bank's market capitalisation to total banking market capitalisation. The individual bank's equity returns are calculated as the daily growth rate of the market value of the bank's equity. The sample period is from 1 January 2007 to 31 March 2022.

the first case reported in the country on 25 January 2020) to 31 March 2022 (i.e., the last trading day before the country transitioned to the endemic phase of COVID-19 on 1 April 2022 announced by the Prime Minister). More importantly, the period is marked by a series of country-level major natural disasters, totalling 35 events identified by the Emergency Events Database (EM-DAT),[4] for which market data are available. EM-DAT defines disaster as "a situation or event that overwhelms local capacity, necessitating a request to the national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction and human suffering" (CRED, 2023b). A disaster is included in the database if it meets at least one of the following criteria: (i) 10 fatalities (including dead and missing); (ii) 100 affected people; or (iii) a declaration of state of emergency or a call for international assistance (CRED, 2023a). The list of the natural disaster periods is provided in Appendix 2. In total, the events caused 186 deaths, 3,017,152 people affected, and USD3.47 billion in damage costs. We use these events to test the hypotheses discussed in Section 2.

We extract the daily data for the banks' equity returns and the state variables used in the quantile regressions for estimating the $\Delta CoVaR$ from Thomson Reuters Datastream.[5] The list of the state variables is provided in Table 1 together with their definitions and descriptive statistics.

4. Results

4.1 Levels of Systemic Risk Contribution and Exposure of Individual Banks

Tables 3 and 4 rank the average estimates for the systemic risk contribution and exposure of each bank as specified in Equations (3) and (9) from lowest to highest, respectively. The estimates are calculated for the entire sample period and five different sub-periods, namely, the 2008 GFC, the 2014 oil price crash, the COVID-19 pandemic, the natural disaster days, as defined in Section 3, as well as the periods without these financial and climate crises. By including financial crises and the pandemic in the analysis, this study intends to offer a comparative perspective on the relative magnitude and impact of natural disasters on bank systemic risk. This comparison is crucial for understanding the scale of climate disasters in relation to other significant global events, thereby highlighting the importance of addressing climate-related risks with the same urgency and comprehensiveness as man-made financial and health crises. Additionally, we plot the time-varying means of the daily systemic risk estimates in Figure 1, while detailed estimations pertaining to individual banks are provided in Appendix 3.

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[4] EM-DAT is a leading worldwide disaster database, which was created in 1988 through a collaboration between the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Louvain in Belgium and the World Health Organization (WHO). The database is compiled from various reliable sources, including United Nations (UN) agencies, non-governmental organisations, reinsurance companies, research institutes and press agencies. The database is accessible online at https://www.emdat.be/

[5] Note that the state variables used for calculating the $\Delta CoVaR$ measure were not all available until 1 January 2007. Specifically, data on the 10-year Malaysian Government Bond and the S&P Malaysia Corporate Bond Index yields were only available from 1 November 2001 and 1 January 2007, respectively, while others can be extracted from much earlier dates.

Table 3. Average systemic risk contribution estimates by banks

Whole period		GFC		Oil price crash		COVID-19		Natural disasters		Non-crisis	
Bank	$\Delta CoVaR^{s\|i}$	Bank	$\Delta CoVaR^{s\|i}$	Bank	$\Delta CoVaR^{s\|i}$	Bank	$\Delta CoVaR^{s\|i}$	Bank	$\Delta CoVaR^{s\|i}$	Bank	$\Delta CoVaR^{s\|i}$
RHB	1.964	MBSB	3.278	MBSB	1.910	RHB	2.541	RHB	1.916	RHB	1.620
MBSB	2.014	RHB	3.364	RHB	1.911	MBSB	2.55	MBSB	1.973	MBSB	1.709
CIMB	2.102	CIMB	3.530	CIMB	1.979	CIMB	2.707	CIMB	2.058	CIMB	1.758
PUB	2.190	PUB	3.648	PUB	2.057	PUB	2.810	PUB	2.145	PUB	1.840
AFF	2.217	AFF	3.706	AFF	2.108	AFF	2.847	AFF	2.177	AFF	1.855
BIMB	2.255	BIMB	3.720	BIMB	2.114	BIMB	2.882	BIMB	2.212	BIMB	1.904
HLB	2.271	HLB	3.738	HLB	2.114	HLB	2.901	HLB	2.225	HLB	1.921
MYB	2.427	MYB	3.926	MYB	2.342	MYB	3.059	MYB	2.393	MYB	2.059
ALL	2.780	ALL	4.262	ALL	2.678	ALL	3.408	ALL	2.749	AMMB	2.394
AMMB	2.785	AMMB	4.372	AMMB	2.711	AMMB	3.449	AMMB	2.758	ALL	2.418

Notes: This table lists the average values of the daily systemic risk contribution estimates ($\Delta CoVaR^{s|i}$) of individual Malaysian banks in ascending order for the entire sample period from 1 January 2007 to 31 March 2022 and five sub-sample periods: (i) the GFC period from 2 August 2007 to 31 March 2009); (ii) the oil price crash period from 25 July 2014 to 11 February 2016; (iii) the COVID-19 pandemic period from 27 January 2020 to 31 March 2022; (iv) the natural disaster periods listed in Appendix 2; and (v) the non-crisis period, which spans all trading days during the sample period except those in (i) to (iv).

Table 4. Average systemic risk exposure estimates by banks

Whole period		GFC		Oil price crash		COVID-19		Natural disasters		Non-crisis	
Bank	$\Delta CoVaR^{i\|s}$	Bank	$\Delta CoVaR^{i\|s}$	Bank	$\Delta CoVaR^{i\|s}$	Bank	$\Delta CoVaR^{i\|s}$	Bank	$\Delta CoVaR^{i\|s}$	Bank	$\Delta CoVaR^{i\|s}$
MYB	2.811	MYB	4.132	MYB	2.440	MYB	3.422	MYB	2.711	MYB	2.528
RHB	3.390	RHB	4.606	AFF	3.194	RHB	3.913	RHB	3.322	RHB	3.103
HLB	3.507	BIMB	4.641	RHB	3.252	BIMB	4.110	HLB	3.447	HLB	3.132
BIMB	3.681	HLB	5.115	HLB	3.272	HLB	4.216	BIMB	3.569	PUB	3.218
PUB	3.704	AFF	5.547	BIMB	3.428	PUB	4.601	PUB	3.666	BIMB	3.479
AFF	3.831	PUB	5.718	PUB	3.477	AFF	4.646	AFF	3.671	AFF	3.486
AMMB	4.269	AMMB	6.167	AMMB	4.450	AMMB	5.006	AMMB	4.245	AMMB	3.766
ALL	5.285	ALL	7.015	ALL	4.987	ALL	6.061	ALL	5.203	CIMB	4.694
CIMB	5.387	CIMB	7.929	CIMB	5.666	CIMB	6.412	CIMB	5.458	ALL	4.886
MBSB	6.471	MBSB	9.838	MBSB	6.056	MBSB	7.922	MBSB	6.391	MBSB	5.677

Notes: This table lists the average values of the daily systemic risk exposure estimates ($\Delta CoVaR^{i|s}$) of individual Malaysian banks in ascending order for the entire sample period from 1 January 2007 to 31 March 2022 and five sub-sample periods: (i) the GFC period from 2 August 2007 to 31 March 2009); (ii) the oil price crash period from 25 July 2014 to 11 February 2016; (iii) the COVID-19 pandemic period from 27 January 2020 to 31 March 2022; (iv) the natural disaster periods listed in Appendix 2; and (v) the non-crisis period, which spans all trading days during the sample period except those in (i) to (iv).

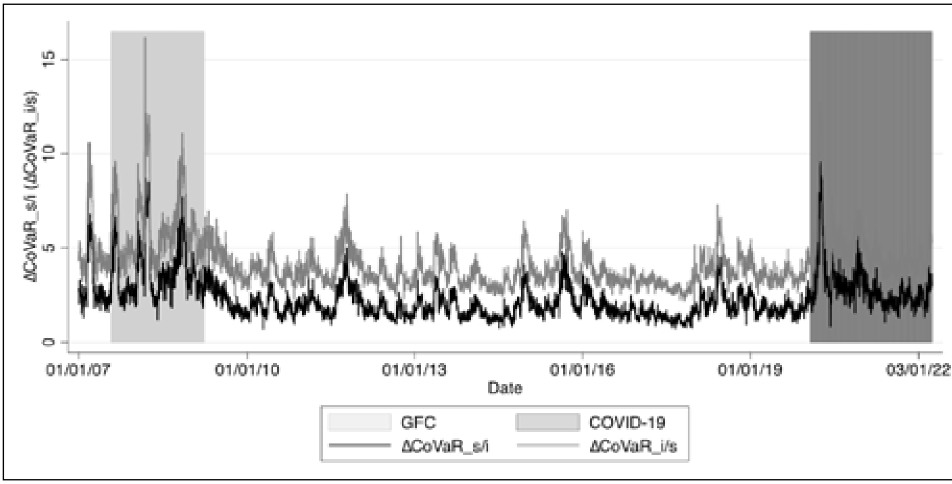

Figure 1. Evolution of the average systemic risk contribution and exposure of Malaysian listed banks

Notes: The figure displays the unweighted means of daily $\Delta CoVaR_{q,t}^{s|i}$ and $\Delta CoVaR_{q,t}^{i|s}$ of listed banks in Malaysia over the entire sample period from 1 January 2007 to 31 March 2022. The solid bars mark two crisis periods: (i) the GFC period from 2 August 2007 to 31 March 2009, and (ii) the COVID-19 pandemic from 27 January 2020 to 31 March 2022.

The results presented in Table 3 demonstrate that banks contribute more risk to the banking system during periods of natural disaster events compared to non-crisis periods. These findings are consistent with previous studies conducted by Wu et al. (2023) and Curcio et al. (2023) concerning Chinese and US listed banks, respectively. Notably, AMMB shows the highest increase, rising from 2.394 to 2.749, while MBSB displays the smallest change, escalating from 1.709 to 1.973. However, these increments have been relatively modest, especially when contrasted with the peak levels witnessed during the GFC and the COVID-19 pandemic as illustrated in Figure 1. It is evident that the risk contributions to the banking system by each individual bank exhibit a considerable degree of similarity, with no single bank demonstrating a pronounced dominance in contribution, even during natural disaster periods. For example, the largest systemic risk contribution is 2.758 by AMMB, and the smallest is 1.916 by RHB. Moreover, the gap in the systemic risk contribution during occurrences of natural disasters further decreases when contrasting the largest bank, MYB, whose market capitalisation surpasses the combined total of all banks below the median level, with the smallest bank in the country, AFF.

When comparing Tables 3 and 4, it can be seen that all banks are exposed to systemic risk at a greater level in comparison to their corresponding systemic risk contributions throughout the full sample period, as well as within different sub-sample periods, including instances of disaster events. This implies a high degree of interconnectedness within the banking system, wherein even if an individual bank manages its risks well internally, it remains susceptible to risks emanating from other banks or the system as a whole. This result has important implications for banks' risk management and regulation, underscoring the need for a holistic approach to systemic risk induced by climate disaster events, where individual bank actions are considered within the broader context of the entire financial system. Moving forward, regulatory frameworks for climate risk mitigation and adaptation must focus not only on the stability of individual banks but also on the resilience of the entire banking system in the face of climate catastrophes.

Furthermore, a higher spread between the largest and smallest values of $\Delta CoVaR^{i|s}$ (i.e., between MBSB at 6.391 and MYB at 2.711) indicates that there exists a discernible variation in the systemic risk impact across different banks. It is also noticeable that during natural disaster periods, among the banks with lower levels of exposure, there is a tendency for them to exhibit a larger contribution to systemic risk. This trend is exemplified by entities like MBSB and CIMB (i.e., ranked second and third in Table 3 and last and second-to-last in Table 4, respectively), while RHB (i.e., ranked first in Table 3 and second in Table 4) stands as an exception to this pattern. This finding suggests that regulators need to account for the broader and more nuanced systemic implications of climate risks, beyond just direct exposure metrics. Banks that are less exposed, appearing less vulnerable at first glance, might still be heavily involved in sectors or regions that are significantly impacted by climate events, thereby transmitting risk through their financial activities (e.g., interbank lending) and relationships.

The summary statistics of the $\Delta CoVaR$ estimations presented in Table 5 conclude the discussion about the findings in the previous two tables. First, on average, banks face

Table 5. Summary statistics of systemic risk contribution and exposure estimates

Panel A: Systemic risk contribution, $\Delta CoVaR^{s|i}$						
	Whole period	GFC	Oil price crash	COVID-19	Natural disasters	Non-crisis
Mean	2.300	3.754	2.192	2.915	2.260	1.948
Std. dev.	1.148	1.515	0.832	1.317	0.943	0.774
Min.	0.202	0.712	0.463	0.289	0.446	0.202
Max.	11.741	11.741	5.742	10.691	6.368	7.464
Kurtosis	10.039	4.297	3.411	10.738	3.461	8.211
Skewness	2.124	1.164	0.847	2.454	0.859	1.645
Panel B: Systemic risk exposure, $\Delta CoVaR^{i|s}$						
Mean	4.234	6.071	4.022	5.031	4.168	3.780
Std. dev.	1.867	2.676	1.553	2.146	1.634	1.376
Min.	0.150	1.382	1.206	1.454	0.567	0.150
Max.	24.804	24.804	12.505	22.453	13.243	17.221
Kurtosis	13.440	7.507	4.707	14.613	5.363	9.063
Skewness	2.350	1.725	1.162	2.618	1.271	1.704

Notes: Panel A of this table reports the summary statistics for daily systemic risk exposure estimates ($\Delta CoVaR^{i|s}$) of individual Malaysian banks for the entire sample period from 1 January 2007 to 31 March 2022 and five sub-sample periods: (i) the GFC period from 2 August 2007 to 31 March 2009); (ii) the oil price crash period from 25 July 2014 to 11 February 2016; (iii) the COVID-19 pandemic period from 27 January 2020 to 31 March 2022; (iv) the natural disaster periods listed in Appendix 2; and (v) the non-crisis period, which spans all trading days during the sample period except those in (i) to (iv). Panel B presents those for the banks' systemic risk exposure estimates ($\Delta CoVaR^{i|s}$).

more risk spillover from the banking system than the risk they have contributed to the system in all periods. Second, the magnitudes of both systemic risk measures are higher during periods of natural disasters than during normal periods. Nevertheless, they remain lower in contrast to those observed during the GFC and the COVID-19 pandemic periods. Lastly, the min-max range and standard deviation values reveal that the extent of the heterogeneity in the risk contribution from an individual bank to the overall system is lesser than that observed in the impact of system risk on an individual bank.

4.2 Changes in Bank Systemic Risk Contribution and Exposure

To begin with, we compute the differences in the levels of bank systemic risk contribution and exposure before, during and after the natural disaster events. Our analysis reveals that 26 out of the observed natural disaster events (74.3%) witness an increase in the banks’ contribution to systemic risk, either during the event or in the aftermath. As far as the bank systemic risk exposure is concerned, the count of events found significant is slightly lower, specifically totalling 24 occurrences (68.6%). To break these figures down, the banks contribute and are exposed to systemic risk more after the events (i.e., 22 and 24 events, respectively) as compared to during the events (i.e., 16 and 17 events, respectively).

Next, Table 6 presents the results of the Wilcoxon signed rank sum test conducted to validate the null hypotheses deliberated in Section 2. These hypotheses are geared towards determining how quickly the levels of the systemic risk contribution and exposure of the Malaysian banks react to natural disasters. For each of the null hypotheses, we calculate the percentage of natural disaster events for which we reject the hypothesis at different confidence levels, 1%, 5% and 10%. The results for each of the 35 natural disaster events are provided in Appendix 2.

Table 6. Bank systemic risk responses to natural disasters: Wilcoxon signed rank sum test

Panel A: Percentage of rejection of the null hypothesis for banks’ contribution to systemic risk			
	1%	5%	10%
$H_0 : \Delta CoVar^{s\|i}_{t:\,t+h} \le \Delta CoVar^{s\|i}_{t-h-1:t-1}$	40.00	40.00	40.00
$H_0 : \Delta CoVar^{s\|i}_{t+h+1:t+2h+1} \le \Delta CoVar^{s\|i}_{t-h-1:t-1}$	37.14	42.86	42.86
$H_0 : \Delta CoVar^{s\|i}_{t+h+1:t+2h+1} \le \Delta CoVar^{s\|i}_{t:\,t+h}$	22.86	37.14	40.00
Panel B: Percentage of rejection of the null hypothesis for banks’ exposure to systemic risk			
$H_0 : \Delta CoVar^{i\|s}_{t:\,t+h} \le \Delta CoVar^{i\|s}_{t-h-1:t-1}$	31.43	40.00	42.86
$H_0 : \Delta CoVar^{i\|s}_{t+h+1:t+2h+1} \le \Delta CoVar^{i\|s}_{t-h-1:t-1}$	31.43	42.86	42.86
$H_0 : \Delta CoVar^{i\|s}_{t+h+1:t+2h+1} \le \Delta CoVar^{i\|s}_{t:\,t+h}$	20.00	34.29	34.29

Notes: Panel A of this table provides the rejection rates (in %) of the null hypotheses for the banks’ systemic risk contribution ($\Delta CoVaR^{s|i}$) estimates, as described in Section 2.2, verified using the Wilcoxon signed rank sum test at confidence levels of 10%, 5% and 1%, respectively. Panel B presents the results for the banks’ systemic risk exposure ($\Delta CoVaR^{i|s}$) estimates.

First, the higher rates of null hypothesis rejection in the second rows of both Panels A and B of Table 6 compared to those in the first rows imply that the market is more inclined to discern the influence of a natural disaster event concerning banks' contribution and exposure to systemic risk once the event has concluded, as opposed to during its unfolding. This finding is consistent with (though our rejection rates are notably higher than) that of Curcio et al. (2023), which analyses a larger sample of US banks and a higher frequency of climate-induced disasters. Second, despite being lower, the rejection rates in the last rows of Panels A and B of the table indicate that there are still cases where the market exhibits either its inaugural or a succeeding reaction after the event ends. Our results challenge the notion of market efficiency, particularly the semi-strong form, which posits that all publicly available information is quickly and accurately reflected in asset prices. The fact that the market appears to have a tendency to recognise the impact of natural disaster events only after they have ended implies inefficiencies in how quickly and accurately climate information is incorporated into prices. This can be further explained from a behavioural finance perspective, which suggests that this delayed market reaction indicates that market participants might exhibit biases or heuristics in their reaction to natural disaster events. These biases could include overconfidence, where investors underestimate the potential impact of climate events, or anchoring, where they rely too heavily on initial information and fail to adjust their expectations in light of new data. Besides, the delayed response aligns with theories of limited attention and underreaction, where market participants do not fully comprehend or react to new climate information immediately. These behavioural tendencies can lead to inefficiencies in the market, where prices do not instantaneously and entirely reflect the true risk posed by climate events, thereby exacerbating systemic risk in the financial system.

5. Concluding Remarks

The primary objective of this study is to assess the systemic risk contribution and exposure of Malaysian banks in the context of natural disasters from January 2007 to March 2022. Employing the $\Delta CoVaR$ metrics, our analysis reveals that natural disasters elevate systemic risk contribution and exposure within the banking sector. However, the extent of this impact is comparatively less severe than the systemic risk spikes observed during previous crises such as the global financial crisis and the COVID-19 pandemic. For comparison, the analysis indicates that the increase in the banks' systemic risk contribution is slightly greater than their exposure during and following the conclusion of such events. In addition, it documents an interesting temporal aspect. Specifically, it suggests that the market is more sensitive to the effects of natural disasters on bank systemic risk measures after the events have ended, not necessarily when they occur. These findings underscore the imperative for regulators to develop well-defined post-disaster financial stability assessment mechanisms to adequately measure and mitigate not only banks' exposure to risk spillovers within the banking sector but also their potential contribution to systemic risks during the recovery phase. It would be beneficial for regulators to require banks to conduct periodic stress tests and scenario analyses that incorporate natural disaster impacts, ensuring that banks maintain adequate capital buffers and robust risk management practices to withstand such shocks. Additionally, enhancing transparency and disclosure requirements around climate risks can help improve market efficiency and reduce information asymmetry, enabling more timely and accurate market responses. As for banks, they might consider leveraging on infrastructure and technology, including artificial intelligence and machine learning, to develop highly predictive models for assessing their natural disaster vulnerabilities and facilitating real-time climate risk monitoring. Furthermore, banks could expand their offering of green financial solutions to support their customers in transitioning towards more environmentally responsible practices.

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Appendix 1. Bank systemic risk responses to natural disasters: Welch's t-test

Panel A: Percentage of rejection of the null hypothesis for banks' contribution to systemic risk			
	1%	5%	10%
$H_0 : \Delta CoVar^{s\|i}_{t:\,t+h} \leq \Delta CoVar^{s\|i}_{t-h-1:t-1}$	31.43	34.29	40.00
$H_0 : \Delta CoVar^{s\|i}_{t+h+1:t+2h+1} \leq \Delta CoVar^{s\|i}_{t-h-1:t-1}$	34.29	37.14	40.00
$H_0 : \Delta CoVar^{s\|i}_{t+h+1:t+2h+1} \leq \Delta CoVar^{s\|i}_{t:\,t+h}$	17.14	22.86	25.71
Panel B: Percentage of rejection of the null hypothesis for banks' exposure to systemic risk			
$H_0 : \Delta CoVar^{i\|s}_{t:\,t+h} \leq \Delta CoVar^{i\|s}_{t-h-1:t-1}$	17.14	20.00	22.86
$H_0 : \Delta CoVar^{i\|s}_{t+h+1:t+2h+1} \leq \Delta CoVar^{i\|s}_{t-h-1:t-1}$	11.43	20.00	22.86
$H_0 : \Delta CoVar^{i\|s}_{t+h+1:t+2h+1} \leq \Delta CoVar^{i\|s}_{t:\,t+h}$	5.71	5.71	5.71

Notes: Panel A of this table provides the rejection rates (in %) of the null hypotheses for the banks' systemic risk contribution ($\Delta CoVaR^{s|i}$) estimates, as described in Section 2.2, verified using the Welch's t-test test at confidence levels of 10%, 5% and 1%, respectively. Panel B presents the results for the banks' systemic risk exposure ($\Delta CoVaR^{i|s}$) estimates.

Appendix 2. List of natural disasters in Malaysia during the sample period

Date (DD/MM/YY)	Disaster type	Duration (days)	Location	No. of deaths	No. injured	No. affected	Total damage, CPI adjusted ('000 US$)	Obs.	Null hypo-theses	Diff.	*z*-statistic	
											Systemic risk contribution ($\Delta CoVaR^{s\|i}$)	Systemic risk exposure ($\Delta CoVaR^{i\|s}$)
11/01/07 – 01/02/07	Flood	21	Johor, Pahang	17	n/a	137,533	853,931	140	H_0 (1)	-0.434	-8.318	-8.214
									H_0 (2)	-0.459	-7.840	-8.545
									H_0 (3)	-0.025	-1.283	-0.183
07/12/07 – 21/12/07	Flood	14	Johor, Kelantan, Pahang, Terengganu	29	n/a	29,000	512,359	110	H_0 (1)	0.209	4.544***	3.929***
									H_0 (2)	-0.103	-1.37	-2.79
									H_0 (3)	-0.312	-6.407	-8.182
01/12/08 – 04/12/08	Flood	4	Pahang, Kelantan, Terengganu	n/a	n/a	2,000	n/a	40	H_0 (1)	-0.489	-4.207	-3.401
									H_0 (2)	-1.868	-5.511	-5.35
									H_0 (3)	-1.379	-5.497	-5.484
28/12/08 – 19/01/09	Flood	22	Pahang, Kelantan, Terengganu, Sarawak	n/a	n/a	6,000	n/a	160	H_0 (1)	0.284	5.135***	2.404***
									H_0 (2)	0.301	3.854***	3.400***
									H_0 (3)	0.017	0.900	2.111**
20/11/09 – 27/11/09	Flood	7	Kedah, Terengganu, Kelantan, Perak	n/a	n/a	10,875	n/a	60	H_0 (1)	-0.030	-1.031	-4.284
									H_0 (2)	-0.256	-4.093	-3.364
									H_0 (3)	-0.226	-5.749	-1.288
28/01/11 – 31/01/11	Flood	3	Johor	2	n/a	20,000	n/a	20	H_0 (1)	-0.230	-3.920	-3.547
									H_0 (2)	-0.198	-3.920	-3.883
									H_0 (3)	0.032	1.307*	0.187
01/12/13 – 08/12/13	Flood	7	Kuala Lumpur, Pahang, Terengganu, Johor, Kelantan	4	n/a	75,000	2,513	50	H_0 (1)	0.069	2.939***	-2.988
									H_0 (2)	0.139	3.615***	0.951
									H_0 (3)	0.070	2.283**	3.306***
01/03/14 – 31/03/14	Drought	31	Kedah, Perak, Perlis, Penang, Selangor	n/a	n/a	2,200,000	n/a	210	H_0 (1)	0.628	11.729***	9.422***
									H_0 (2)	0.412	-10.709	-8.925
									H_0 (3)	-0.216	-12.494	-11.824

Appendix 2. Continued

Date (DD/MM/YY)	Disaster type	Duration (days)	Location	No. of deaths	No. injured	No. affected	Total damage, CPI adjusted ('000 US$)	Obs.	Null hypo-theses	Diff.	z-statistic	
											Systemic risk contribution ($\Delta CoVaR^{s\|i}$)	Systemic risk exposure ($\Delta CoVaR^{i\|s}$)
16/12/14 – 30/12/14	Flood	14	Sabah, Kelantan, Pahang, Terengganu, Perak, Johor, Selangor	17	n/a	230,000	351,083	110	H_0 (1)	0.394	7.272***	6.624***
									H_0 (2)	-0.245	4.955***	5.119***
									H_0 (3)	-0.640	-3.634	-3.786
14/01/15 – 20/01/15	Flood	7	Sarawak	1	n/a	3,000	n/a	50	H_0 (1)	0.172	-6.154	-5.517
									H_0 (2)	-0.053	-6.154	-6.154
									H_0 (3)	-0.225	-6.154	-6.135
05/06/15 – 05/06/15	Earthquake	1	Sabah	24	10	10	2	10	H_0 (1)	-0.795	2.803***	2.701***
									H_0 (2)	-1.959	-2.701	2.803***
									H_0 (3)	-1.163	-2.803	-2.191
19/02/16 – 24/02/16	Flood	5	Johor, Melaka, Negri Sembilan, Sarawak	n/a	n/a	6,000	n/a	40	H_0 (1)	-0.037	-1.841	-0.349
									H_0 (2)	0.027	1.680**	3.965***
									H_0 (3)	0.064	2.204**	2.016**
18/07/16 – 19/07/16	Flood	2	Kedah, Penang	n/a	n/a	441	n/a	20	H_0 (1)	-0.477	-3.920	0.261
									H_0 (2)	-0.291	-3.808	1.195
									H_0 (3)	0.186	1.904**	2.352***
28/11/16 – 07/12/16	Flood	9	Terengganu	n/a	n/a	400	n/a	80	H_0 (1)	-0.087	-3.799	0.964
									H_0 (2)	-0.452	-7.655	-4.782
									H_0 (3)	-0.365	-7.655	-6.158
26/12/16 – 07/02/17	Flood	43	Terengganu, Kelantan, Pahang, Johor, Perak, Sabah, Selangor, Malacca	n/a	n/a	30,481	160,955	320	H_0 (1)	-0.148	-5.684	-4.704
									H_0 (2)	-0.131	-4.052	-2.260
									H_0 (3)	0.017	3.816***	2.711***
03/11/17 – 08/11/17	Flood	5	Penang, Kedah, Perak	7	n/a	3500	n/a	40	H_0 (1)	0.805	-2.070	0.229
									H_0 (2)	0.548	5.444***	2.231**
									H_0 (3)	-0.257	5.497***	3.307***

Appendix 2. Continued

Date (DD/MM/YY)	Disaster type	Duration (days)	Location	No. of deaths	No. injured	No. affected	Total damage, CPI adjusted ('000 US$)	Obs.	Null hypo-theses	Diff.	*z*-statistic	
											Systemic risk contribution ($\Delta CoVaR^{s\|i}$)	Systemic risk exposure ($\Delta CoVaR^{i\|s}$)
25/11/17 – 03/12/17	Flood	8	Kelantan, Terengganu	2	n/a	13000	n/a	50	H_0 (1)	0.023	1.134	-0.961
									H_0 (2)	0.012	0.237	2.283**
									H_0 (3)	-0.012	-1.684**	1.964**
18/12/17 – 20/12/17	Storm	3	Sarawak, Sabah	n/a	n/a	426	n/a	30	H_0 (1)	-0.085	4.782***	4.659***
									H_0 (2)	0.205	4.782***	3.980***
									H_0 (3)	0.290	-3.651	-2.684
01/01/18 – 05/01/18	Flood	5	Pahang, Johor, Terengganu	2	n/a	12,000	n/a	50	H_0 (1)	0.823	4.677***	1.704**
									H_0 (2)	0.896	4.638***	5.102***
									H_0 (3)	0.072	0.874	2.071**
03/02/18 – 12/02/18	Flood	9	Sarawak	n/a	n/a	4,900	n/a	60	H_0 (1)	0.239	5.691***	5.389***
									H_0 (2)	0.290	6.736***	6.625***
									H_0 (3)	0.050	1.141	1.060
02/06/19 – 06/06/19	Flood	4	Sarawak	n/a	n/a	1,000	n/a	40	H_0 (1)	0.348	5.497***	4.597***
									H_0 (2)	0.315	4.839***	5.040***
									H_0 (3)	-0.032	-0.269	-1.048
30/11/19 – 06/12/19	Flood	7	Johor, Kelantan, Pahang, Terengganu	2	n/a	15,000	n/a	50	H_0 (1)	0.249	2.978***	2.051**
									H_0 (2)	0.115	3.441***	-3.499
									H_0 (3)	-0.135	-1.144	-3.673
18/12/19 – 19/12/19	Flood	2	Terengganu, Kelantan	n/a	n/a	4,065	n/a	20	H_0 (1)	-0.349	-3.920	-0.187
									H_0 (2)	0.281	3.584***	1.232
									H_0 (3)	0.630	3.920***	2.800***
25/04/20 – 29/04/20	Flood	4	Sarawak	n/a	n/a	2,000	n/a	30	H_0 (1)	-0.986	-4.782	-4.288
									H_0 (2)	-1.716	-4.782	-4.782
									H_0 (3)	-0.730	-4.782	-4.700

Appendix 2. Continued

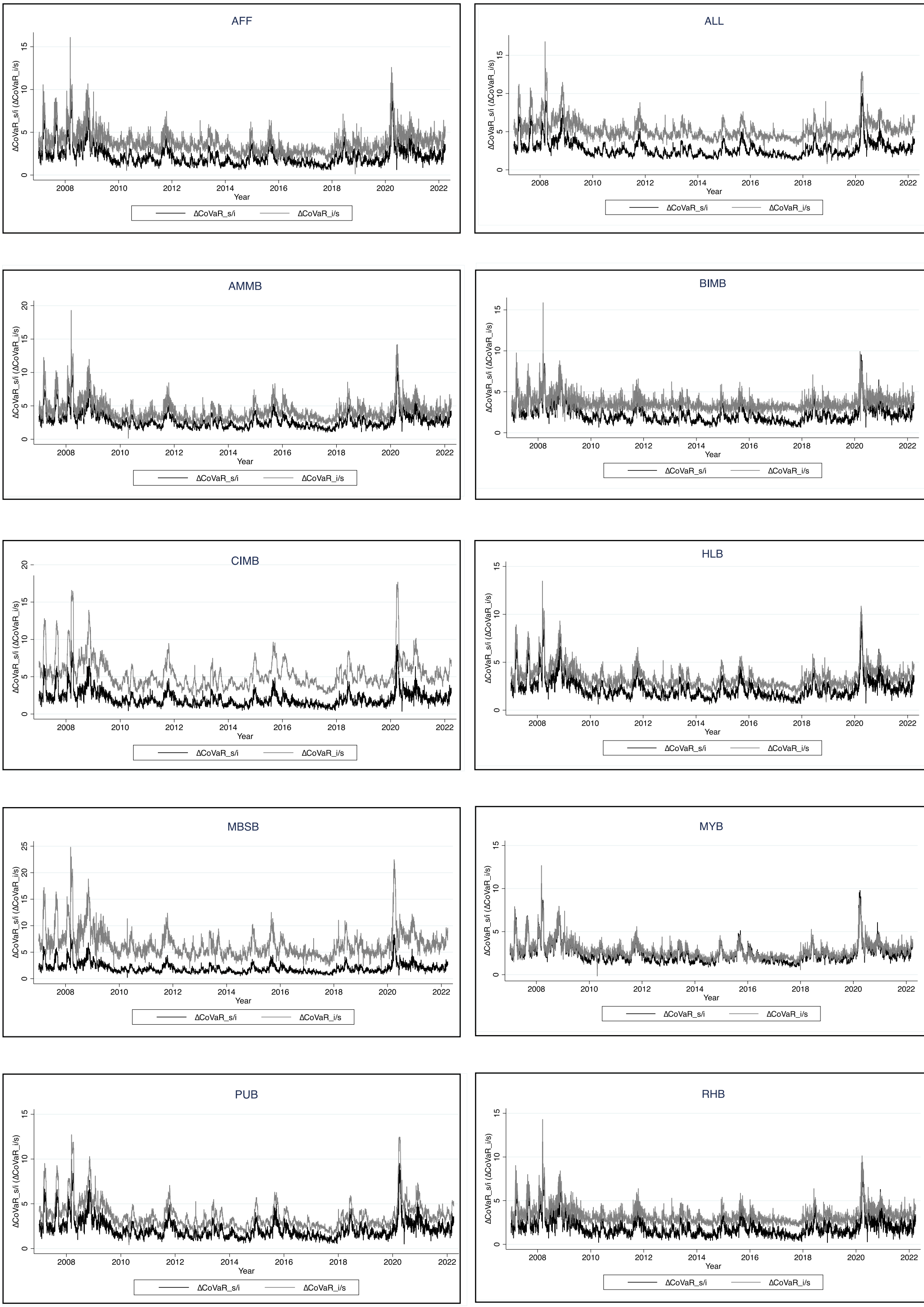
Date (DD/MM/YY)	Disaster type	Duration (days)	Location	No. of deaths	No. injured	No. affected	Total damage, CPI adjusted ('000 US$)	Obs.	Null hypo-theses	Diff.	z-statistic	
											Systemic risk contribution ($\Delta CoVaR^{s\|i}$)	Systemic risk exposure ($\Delta CoVaR^{i\|s}$)
20/06/20 – 25/06/20	Flood	5	Johor	n/a	n/a	1,210	n/a	40	H_0 (1)	0.343	-2.419	-1.640
									H_0 (2)	-0.280	-4.785	-3.764
									H_0 (3)	-0.623	-4.597	-2.379
27/06/20 – 01/07/20	Flood	4	Sabah, Sarawak	n/a	n/a	9,000	7,689	30	H_0 (1)	-0.357	-3.651	-3.486
									H_0 (2)	-0.922	-4.083	-4.638
									H_0 (3)	-0.566	-4.782	-3.671
09/10/20 – 09/10/20	Flood	1	Sabah	n/a	n/a	400	n/a	10	H_0 (1)	-0.186	-2.803	-1.886
									H_0(2)	-0.669	-2.803	-1.886
									H_0 (3)	-0.484	0.005***	0.059***
20/12/20 – 21/12/20	Flood	2	Terengganu, Kelantan, Pahang	n/a	n/a	9,273	n/a	10	H_0 (1)	-1.410	2.803***	2.803***
									H_0 (2)	-0.931	-2.803	0.009***
									H_0 (3)	0.479	0.005	-2.803
02/01/21 – 15/01/21	Flood	14	Johor, Pahang, Terengganu, Sabah, Kelantan, Selangor, Perak, Sarawak	8	n/a	32,776	n/a	100	H_0 (1)	0.095	-8.273	-8.028
									H_0 (2)	0.844	-8.616	-8.551
									H_0 (3)	0.749	3.456***	0.994
20/05/21 – 03/06/21	Flood	14	Sabah, Sarawak, Melaka	n/a	n/a	5,782	n/a	110	H_0 (1)	-0.102	-3.959	-5.071
									H_0 (2)	-0.154	0.860	-3.043
									H_0 (3)	-0.052	4.028***	1.144
17/08/21 – 19/08/21	Flood	3	Kedah	7	3	4,825	n/a	30	H_0 (1)	0.527	1.183	-1.142
									H_0 (2)	0.267	4.782***	4.659***
									H_0 (3)	-0.260	4.782***	4.782***
07/09/21 – 17/09/21	Flood	10	Sabah, Johor, Sarawak	2	n/a	255	n/a	90	H_0 (1)	-0.910	8.239***	5.877***
									H_0 (2)	-0.769	2.911***	1.728**
									H_0 (3)	0.141	-3.651	-2.682

Appendix 2. Continued

Date (DD/MM/YY)	Disaster type	Duration (days)	Location	No. of deaths	No. injured	No. affected	Total damage, CPI adjusted ('000 US$)	Obs.	Null hypo-theses	Diff.	*z*-statistic	
											Systemic risk contribution ($\Delta CoVaR^{s\|i}$)	Systemic risk exposure ($\Delta CoVaR^{i\|s}$)
20/10/21 – 22/10/21	Flood	3	Kedah, Malacca, Negeri Sembilan, Selangor, Kuala Lumpur	n/a	n/a	1,000	n/a	30	H_0 (1)	0.200	-0.134	1.882**
									H_0 (2)	0.663	-2.972	1.820**
									H_0 (3)	0.463	-1.347	-1.306
17/12/21 – 03/01/22	Flood	17	Pahang, Selangor, Terengganu, Kelantan, Johor, Malacca, Negeri Sembilan, Sabah, Sarawak, Kuala Lumpur	56	n/a	120,000	1,576,841	100	H_0 (1)	-0.154	4.567***	3.158***
									H_0 (2)	0.038	8.587***	8.498***
									H_0 (3)	0.192	7.092***	8.645***
25/02/22 – 28/02/22	Flood	4	Kelantan, Pahang and Terengganu	6	n/a	26,000	240	20	H_0 (1)	-0.079	-1.680	1.568*
									H_0 (2)	0.230	1.867**	0.672
									H_0 (3)	0.309	1.867**	0.224

Notes: This table provides the list of natural disasters that happened in Malaysia during the sample period (1 January 2007 to 31 March 2022) taken from EM-DAT. Note that the only earthquake event on 5 June 2015 is not directly caused by climate change. $H_0(1)$, $H_0(2)$ and $H_0(3)$ represents the null hypotheses in Eqs. (10) (i.e., H_0: $\Delta CoVaR_{t:t+h} \leq \Delta CoVaR_{t-h-1:t-1}$), (12) (i.e., H_0: $\Delta CoVaR_{t+h+1:t+2h+1} \leq \Delta CoVaR_{t-h-1:t-1}$), and (14) (i.e., H_0: $\Delta CoVaR_{t+h+1:t+2h+1} \leq \Delta \mathrm{CoVaR}_{t:t+h}$), respectively. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Appendix 3. Evolution of individual banks' contribution and exposure to systemic risk



Note: The figures display the daily $\Delta CoVaR_{q,t}^{s|i}$ and $\Delta CoVaR_{q,t}^{i|s}$ for individual listed banks in Malaysia over the entire sample period from 1 January 2007 to 31 March 2022.