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by

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Climate Risk and Financial Stability: A Systemic Risk Perspective from Thailand

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Abstract

Understanding the impact of climate risks on financial stability is crucial for ensuring the resilience of banking sectors, particularly in economies exposed to climate change. This paper investigates how transition and physical risks influence systemic risk in Thailand's banking sector. Transition risks are analyzed using the Fama-French multi-factor asset pricing model to estimate the risk premium of brown industries relative to green industries, termed Brown-minus-Green (BMG). Physical risks are assessed using the Standardized Precipitation Evapotranspiration Index (SPEI), an indicator of flood and drought conditions. Systemic risk at the bank level is measured using conditional value-at-risk (CoVaR). Panel regressions are employed to examine the relationship between climate risks and systemic risk. The results reveal that transition risks, as captured by the BMG factor, significantly heighten systemic risk among Thai banks, emphasizing their critical role in financial vulnerabilities. Additionally, physical risks, particularly those associated with flood exposure, create substantial challenges for bank portfolios. These findings highlight the importance of integrating transition and physical risk indicators into regulatory monitoring frameworks to enhance financial stability. Furthermore, Thai commercial banks can apply these insights to conduct climate stress tests and develop strategies for managing climate-related risks more effectively.

Keywords: climate risk, systemic risk, Thailand, banking sector, BMG, SPEI, CoVar

JEL classification: C58, G12, G21, Q54

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1. Introduction

Climate change poses a major challenge, threatening to significantly impact both the economy and the financial sector. Weather, climate, and water-related disasters negatively affect societies and economies. According to the World Meteorological Organization (WMO), approximately 2.1 million lives were lost, and economic losses totaling around USD 4.3 trillion were incurred globally due to weather, climate, and water-related hazards between 1970 and 2021. Climate change introduces two primary types of risks: physical and transition risks (Grippa and Demekas, 2021). Physical risks refer to potential economic costs and financial losses resulting from long-term gradual changes in climate or climate-related hazards (e.g., heat waves, extreme precipitation, floods, droughts, etc.). Transition risks arise from policy and legal changes, technological progress, and market developments in response to climate-related financial risks (Wu et al., 2023).

Physical and transition risks can adversely impact financial institutions through mechanisms such as losses in the value of financial portfolios, increases in claims paid by insurers, or reductions in the creditworthiness of borrowers. These shocks can threaten financial stability, particularly when they occur simultaneously or when extreme shocks propagate through the network of financial interconnections. These threats to the financial system stemming from climate risks are collectively referred to as "systemic climate risks." This paper employs an empirical framework that integrates climate and stock market data to assess the influence of climate risks on systemic risk within the financial sector.

Regarding physical risks, studies by Caldeira and Brown (2019), Cai et al. (2018), and Qiu and Zhao (2019) show that the frequent occurrence of extreme weather events reduces production efficiency. Similarly, research by Yannis et al. (2018), Bovari et al. (2018), and Huang et al. (2018) finds that business profitability and firms' credit costs are adversely affected by climate extremes, contributing to higher loan defaults, reduced cash flows, and asset devaluation, which in turn increase risks in the banking sector. Transition risks arise during the transition to a low-carbon economy. Policies addressing climate change, such as carbon pricing measures, increase costs for companies with high energy consumption and greenhouse gas emissions. Furthermore, factors such as shifts in climate policy, technological advancements, regulatory changes, legal exposure, and evolving consumer preferences also contribute to transition risks (Krueger et al., 2020; Stroebel and Wurgler, 2021). Systemic risks pertain to the potential for disruptions within a financial system that can lead to widespread instability. Jourde and Moreau (2023) provide a broad measure of systemic climate risks based on market data, capturing the effects of climate risks on the financial sector.

This paper examines the relationship between climate risks and systemic risks. This is essential for developing robust strategies to mitigate potential impacts and enhance resilience. Both physical and transition risks are analyzed using climate and financial data. Transition risk is assessed through the Fama-French multi-factor models, calculating the risk premium for brown versus green industries using a long-short portfolio (BMG). Physical risk is captured using the Standardized Precipitation Evapotranspiration Index (SPEI), while systemic risk at the bank level is measured using the conditional value-at-risk (CoVaR) based on trading data from the Stock Exchange of Thailand. Panel regressions, controlling for Fama-French (2015) risk factors and macroeconomic variables, are used to quantify the impact of climate risks on systemic risk, providing insights into how climate risks affect Thai banks and informing regulators about the implications for financial stability.

This paper offers important contributions to the literature on climate risks and financial stability. It incorporates both transition and physical risks into the analysis of systemic risk in the banking sector, using SPEI to capture physical risks and BMG portfolios to highlight the financial sector's exposure to transition risks. By addressing these dimensions, the paper bridges the gap between climate risk research and systemic risk frameworks, providing valuable insights into the challenges posed by climate risks for financial stability in Thailand.

The rest of the paper is organized as follows: the next section reviews related studies on the impacts of physical and transition risks on the financial sector. Section 3 discusses the methods and data used to capture transition and physical risks, measure systemic risk, and conduct panel regressions to quantify the effects of climate risks on systemic risk. Section 4 presents the results of the analysis, and Section 5 concludes.

2. Review of literature

The literature highlights several unique characteristics of climate risk. First, climate risk is identified as systemic and non-linear (Battiston et al., 2017; Dafermos, 2021; Monasterolo, 2020) and is characterized by fat-tail distributions (e.g., Weitzman, 2009; Ackerman, 2017). This implies that if climate risks are not promptly addressed, they may trigger tipping points within ecosystems (Steffen et al., 2018; Lenton et al., 2019), leading to prolonged socio-ecological and economic crises. Such crises may cause hysteresis effects, preventing environmental and economic systems from returning to their pre-crisis states and significantly impacting financial stability. Furthermore, the interconnectedness of actors plays a critical role in how these risks materialize; actions that seem optimal at the individual level can result in sub-optimal outcomes at the systemic level. Second, climate risk is endogenous, meaning that the realization of worst-case scenarios depends on the risk perceptions of key agents (such as policymakers and investors) and their subsequent actions (Battiston, 2019). Third, climate risk simultaneously involves and affects various dimensions of the food-water-energy nexus and related socio-economic activities through multiple channels, increasing the complexity of its impacts and complicating policy responses (Howarth and Monasterolo, 2016).

The literature has highlighted two main channels through which climate change affects financial stability: physical and transition risks (Carney, 2015; Battiston et al., 2021). Under physical risks, damages to firms' assets and production capacity caused by climate change may increase banks' credit risks, result in losses for the insurance sector, and weaken the financial position of governments. In terms of transition risks, a shift to a low-carbon economy can cause unexpected changes in asset prices and defaults across various asset classes, leading to financial shocks for asset managers, investors, and banks. According to Chabot and Bertrand (2023), as the economy transitions away from fossil fuels—driven by climate policies, technological advancements, or shifts in consumer preferences—this process creates opportunities for some industries while posing significant risks to others, particularly those reliant on fossil fuels. These risks can result in potential losses in profits and value for the affected companies and the banks that finance them. Businesses whose revenues depend on fossil fuel production, such as companies involved in extracting oil, gas, and coal, may face the issue of stranded assets as a result of the low-carbon transition (Leaton, 2011; Van der Ploeg and Rezai, 2020).

However, the risk is not confined to the fossil fuel sector. Firms in other carbon-intensive or energy-intensive industries, or those relying on fossil fuels as production inputs, may also be significantly impacted (Matikainen and Soubeyran, 2022). These losses can, in turn, negatively affect the value of firms' financial contracts and the financial portfolios exposed to these firms, such as bank loans and the equity and bond holdings of pension funds (Battiston et al., 2017; Stolbova et al., 2018; Semieniuk et al., 2020).

Indeed, physical and transition risks have significant implications for various sectors of the economy, can adversely affect financial institutions, and may pose a threat to financial stability if they occur simultaneously or if extreme shocks are transmitted to other institutions through the network of financial interconnections. According to Jourde and Moreau (2023), these threats to the financial system stemming from climate risks are referred to as "systemic climate risks."

Our work is related to several strands of literature. The first strand examines the impacts of climate risks on financial stability (Carney, 2015; Dietz et al., 2016; Battiston et al., 2017; Liu et al., 2021; Roncoroni et al., 2021). Battiston et al. (2017) highlight the importance of climate stress-testing for financial stability, while Roncoroni et al. (2021) investigate the interplay between climate policy shocks and market conditions, proposing an operational framework for climate stress-testing. Roncoroni et al. (2021) extend the existing climate stress-testing framework for financial systems by incorporating an ex-ante network valuation of financial assets that accounts for both asset price volatility and endogenous recovery rates on interbank assets. Additionally, their study considers the dynamics of indirect contagion among banks and investment funds—key players in the low-carbon transition—through exposures to the same asset classes.

The second strand of related literature focuses on systemic risk and financial linkages. Systemic risk is a critical concern that has received substantial attention due to the danger of distress in one bank amplifying fear and panic within the financial system during periods of stress. This can lead to the failure of other financial institutions and potentially trigger a financial crisis. Estimating the level of systemic risk and financial linkages among financial institutions is, therefore, essential. Such estimates can inform bank supervisors and regulators in designing more tailored policies and regulations. According to Roengpitya and Rungcharoenkitkul (2011), the sources of systemic risk can be classified into three categories: (i) instruments such as loans, bonds, equities, and derivatives; (ii) markets, such as bilateral over-the-counter trading; and (iii) institutions, including banks, securities dealers, and insurance companies. The literature on estimating systemic risk and financial linkages often relies on credit default swap (CDS) data, as CDS data reflect the default dependence among financial institutions (Chan-Lau et al., 2009a, b; Giesecke and Kim, 2009; Segoviano and Goodhart, 2009). However, CDS data capture only credit risk. To estimate both systemic risk and financial linkages more comprehensively, Adrian and Brunnermeier (2008) proposed using stock market data to calculate the conditional value-at-risk (CoVaR). CoVaR measures the degree of "risk externalities" that an individual institution imposes on the broader financial system. The underlying hypothesis in Adrian and Brunnermeier's (2008) approach is that, under market efficiency, stock market prices should reflect all types of risks facing financial institutions. Roengpitya and Rungcharoenkitkul (2011) applied this approach to stock market data from 1996 to 2009 to quantify systemic risk and financial linkages in the Thai banking system using the concept of CoVaR. Their findings revealed that individual banks imposed additional risk on the overall system, particularly during the Asian financial crisis and subsequent periods, with larger banks contributing more significantly to systemic risk. However, the existing literature has yet to incorporate the role of climate risks in estimating systemic risk and financial linkages.

The study by Jourde and Moreau (2023) utilized a market-based framework to examine systemic climate risks in the financial sector. Their measure of systemic risk applied methods proposed by Adams et al. (2014), Adrian and Brunnermeier (2016), and Kelly and Jiang (2014). Specifically, Jourde and Moreau (2023) estimated time-varying Value-at-Risk (VaR) from the stock returns of financial institutions using a GARCH model, under the assumption that equity returns provide information about the risks faced by financial institutions. Tail risk measures were also employed to assess whether climate risks pose a threat to financial stability. Principal component analysis was used to estimate systemic risks, capturing common shifts in the tails of financial institution returns, i.e., tail risk dependence within the financial sector. In particular, Jourde and Moreau (2023) constructed two long-short factor-mimicking portfolios based on carbon emission intensities and physical risk scores. For transition risks, the long and short positions were determined by carbon emission intensity (Giglio et al., 2021), defined as reported and estimated Scopes 1 and 2 emissions divided by net sales. The Brown-minus-Green (BMG) factor captures the returns associated with the transition risk factor. These factors aim to quantify the impact of climate shocks on the value of non-financial firms, to which financial institutions are exposed through loans, portfolio holdings, or insurance contracts.For physical risks, studies such as Jourde and Moreau (2023) sort firms based on physical scores provided by Trucost, which aggregates data on seven types of climate hazards: cold waves, floods, heat waves, hurricanes, sea level rise, water stress, and wildfires. Jourde and Moreau (2023) employed the Composite Moderate 2050 score, representing physical risk exposure in 2050 under the RCP4.5 pathway. The Vulnerable-minus-Safe (VMS) factor captures the returns associated with the physical risk factor. Their findings indicate that transition risks related to the shift toward a low-carbon economy significantly influence systemic risk to a greater extent than physical risks, such as natural disasters.

In this paper, we calculate the risk premium of brown industries relative to green industries using a long-short portfolio (Brown-minus-Green or BMG) following the methodology of Jourde and Moreau (2023). However, unlike Jourde and Moreau (2023), who captured physical risk using the Composite Moderate 2050 score representing physical risk exposure in 2050, we capture physical risk using the Precipitation Evapotranspiration Index (SPEI). Systemic risk at the bank level is measured using the conditional value-at-risk (CoVaR), derived from trading data on the Stock Exchange of Thailand. This approach to constructing systemic risk follows the methodology outlined in Roengpitya and Rungcharoenkitkul (2011).

3. Methods and Data

3.1 Systemic risk measurement

In this paper, the trading information from equity market is used to gauge the systemic risk for each commercial bank. In the Stock Exchange of Thailand (SET), there are twelve stocks listed in the banking sector index of SET. We exclude Thai credit bank, which listed in SET since February 2024, due the limited trading data. Table 1 shows the list of commercial banks listed in the Stock Exchange of Thailand ranked by their market capitalization. We classified banks into two categories: big bank for banks with market capitalization over 100,000 million baht and small bank for banks with market capitalization below 100,000 million baht and banks usually specialized in some services, such as TISCO Financial Group, Katnakin Phatra Bank and LH Financial Group, which specialize in auto leasing, private banking services and housing loan, respectively.

Table 1: Classification of banks according to the market capitalization

No.	Classification	Banks	Name Abbreviations	Market Capitalization (as of 30 Sep 2024)
1	Big banks	Siam Commercial Bank	SCB	367,015
2		Kasikorn Bank	KBANK	355,399
3		Krungthai Bank	KTB	287,907
4		Bangkok Bank	BBL	287,281
5		Bank of Ayudhya	BAY	193,089

No.	Classification	Banks	Name Abbreviations	Market Capitalization (as of 30 Sep 2024)
6		TMB Thanachart bank	TTB	191,677
7	Small specialized banks	Tisco Financial Group	TISCO	77,262
8		Thanachart Capital	TCAP	52,955
9		Kiatnakin Phatra Bank	KKP	43,185
10		CIMB Thai Bank	CIMBT	18,456
11		LH Financial Group	LHFC	17,794

Source: Stock Exchange of Thailand

To construct a measure of systemic risk among financial institutions, the common variation in tail risk is considered. We adopt the CoVaR (Conditional Value at Risk) framework introduced by Adrian and Brunnermeier (2016), which measures systemic risk by capturing the risk of the financial system conditional on a particular institution being in distress. Specifically, the CoVaR of the financial system, conditional on institution *i* at the *q%* quantile, is defined as the value at risk (VaR) of the system when institution *i* is in distress. The ΔCoVaR is defined as the difference between the CoVaR conditional on institution *i* being in distress and the CoVaR conditional on institution *i* being in its median state:

$$\Delta CoVaR_i^{sys} = CoVaR_i^{sys}(i \text{ in distress}) - CoVaR_i^{sys}(i \text{ in median state})$$

This measures the change in systemic risk due to the distress of institution *i*. The CoVaR and ΔCoVaR are estimated using quantile regression, a powerful tool to capture the behavior of the financial system's tail risks. The quantile regression allows for estimating the conditional quantiles of the financial system's losses given the losses of an individual institution. Formally, the CoVaR of the financial system at the *q%-quantile* conditional on institution *i*'s distress is obtained by estimating the following quantile regression model:

$$X_q^{sys} = \alpha_q + \beta_q X^i$$

where X_q^{sys} represents the predicted value of the system's losses at the *q%-quantile* given the losses of institution *i* (denoted by X^i). The CoVaR of the financial system conditional on institution *i*'s distress, $CoVaR^q_{sys|i}$, is the predicted value of the financial system's losses when the institution is at its Value at Risk level $X^i = VaR_q^i$:

$$CoVaR^q_{sys|i} = \alpha_q + \beta_q VaR^q_i$$

To compute ΔCoVaR, we calculate the difference between the CoVaR when institution *i* is in distress (i.e., at its VaR level) and the CoVaR when the institution is in its median state:

$$\Delta CoVaR_i^{sys} = \beta_q (VaR_q^i - VaR_{50}^i)$$

In this approach, the coefficients from the quantile regression (α_q and β_q) determine the relationship between the losses of institution *i* and the financial system. The quantile regression method is advantageous because it effectively captures the tail dependency between the two variables, which is crucial for systemic risk analysis.

3.2 Climate Risk Factors

Next, we construct the climate risk factors that disentangle between transition and physical risks. Transition risk refers to policy and legal changes, technological progress, and market developments in response to the financial risks arising from climate change, while physical risk refers to the potential economic costs and financial losses due to long-term gradual changes in climate or climate-related hazards (e.g., heat waves, extreme precipitation, flood, drought, etc.). Physical and transition risks can adversely affect financial institutions through, for example, losses in the value of financial portfolios, increases in claims paid by insurers, or decreases in the creditworthiness of borrowers. In the literature, there are several approaches that can be used in constructing the climate risk factors. Some papers apply the natural language processing to assess the degree of media coverage or the degree of media attention to climate change (Ardia et al., 2022; Engle et al., 2020). Other papers construct a climate stress indicator using investors flows toward sustainable exchange-traded funds (Briere and Ramelli, 2021). The approach used in this paper to construct transition risk factor is along the line of the literature which directly captures the effect of climate characteristics on the returns of non-financial stocks by building a long-short portfolios based on market and environmental variables (Görgen et al., 2020; Hsu et al., 2022). For the physical risk, we use the climate extreme index, specifically the Standardized Precipitation Evapotranspiration Index (SPEI), which takes into account both precipitation and potential evapotranspiration. Thus, the SPEI index can be used as the climate indicator, which can capture both types of climate extremes, i.e., heavy precipitation and drought. Details of how the transition and physical risk factors are constructed are as follows.

3.2.1 Transition risk

The transition risk factor is constructed using the financial market data based on the empirical asset pricing model of Fama and French (1993, 2015). Particularly, we computed the premium of specified risk-factors by forming the portfolio that represent group of equity trading in stock market with the high- and low- risk characteristics. The differences between returns from portfolio forming with high- and low- risk characteristics are interpreted as required returns or risk premiums or discount factors, which can be varied over time. These empirical returns are equivalent to those of the returns from portfolio forming with long positions in the high characteristics risk and short position in the low characteristics risk, hereafter "long and short portfolio". We use the environmental indicators to form a portfolio demonstrating transition risk factors. The long and short positions are determined by their carbon emission intensity[2]. The Brown minus Green (BMG) represents the returns of the transition risk factor. Data on equity return and GHG emission intensity of non-financial equity return are retrieved from Bloomberg.

To estimate the BMG factor, we focus on listed companies and limit our analysis to the top 300 firms by market capitalization. These companies are ranked by their greenhouse gas (GHG) emission intensity per unit of sales, an indicator of carbon efficiency. Based on these rankings, we classify stocks into quintiles, with the first quintile representing the most carbon-intensive (brown) stocks and the bottom quintile representing the least carbon-intensive (green) stocks. The BMG factor is calculated as the difference in returns between the brown and green portfolios, formed by taking a long position in the brown stocks and a short position in the green stocks. These portfolios are rebalanced and updated quarterly to reflect changes in market capitalization and carbon intensity rankings.

3.2.2 Physical risk

In the case of physical risk, unlike other paper such as Jourde and Moreau (2023) that uses the physical scores of climate hazards, such as flood, heatwave, hurricane, sea level rise, water stress and wildfire, this paper uses

[2] It is important to highlight that the carbon emission intensity is considered as a fundamental measure of transition risk. While the carbon emissions intensity is likely to capture transition risks associated with changes in regulation, policies and consumer preferences, it might not be able to reflect the transition risks associated with technological changes (Giglio et al., 2021; Jourde and Moreau, 2023).

the Standardized Precipitation Evapotranspiration Index (SPEI) to capture the physical risk. These characteristics make the SPEI an ideal candidate to quantify drought severity and assess drought impacts across different sectors. In addition, the SPEI has a multi-scalar character, which enables it to be used by different scientific disciplines to detect, monitor and analyze droughts. Similar to other climate indices, such as the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI), the SPEI can measure drought severity according to its intensity and duration, and can identify the onset and end of drought episodes. The procedure to calculate the index is detailed and involves a climatic water balance, the accumulation of deficit/surplus at different time scales, and adjustment to a log-logistic probability distribution (Vicente-Serrano et al., 2010). Mathematically, the SPEI is similar to the standardized precipitation index (SPI), but it includes the role of temperature.

The SPEI is calculated using data of precipitation and atmospheric evaporative demand, and it can be calculated at different time scales (1-48 months) (Vicente-Serrano et al., 2022; Beguería et al., 2014). Figure 1 shows the SPEI at different time scales. The time scales reflect the time periods in which the water balance is cumulated. SPEI1 to SPEI48 correspond with the case in which the water balance is cumulated over 1 to 48 months which capture varying degrees of persistence and severities in climate conditions. According to Han et al. (2021), even though the shorter timescales SPEI, i.e. (1-, 3-, and 6-month SPEI) could reflect the details of droughts or floods better, when the timescale is too short, the extracted drought events are overestimated and tend to last only 1 or 2 months, making it difficult to analyze drought from a longer time perspective. On the contrary, longer timescales SPEI (such as 24- or 48-month SPEI) can reflect drought trends, while the extracted drought events are underestimated and some more detailed information about droughts is smoothed out and lost. Therefore, in this study, the 12-month SPEI or SPEI12 is selected as it not only reflect the long-term trend but also maintain interannual drought changes (Liu et al., 2021). The 12-month SPEI index (SPEI12) represents the water balance cumulated over a year and captures more persistent and severe weather conditions.

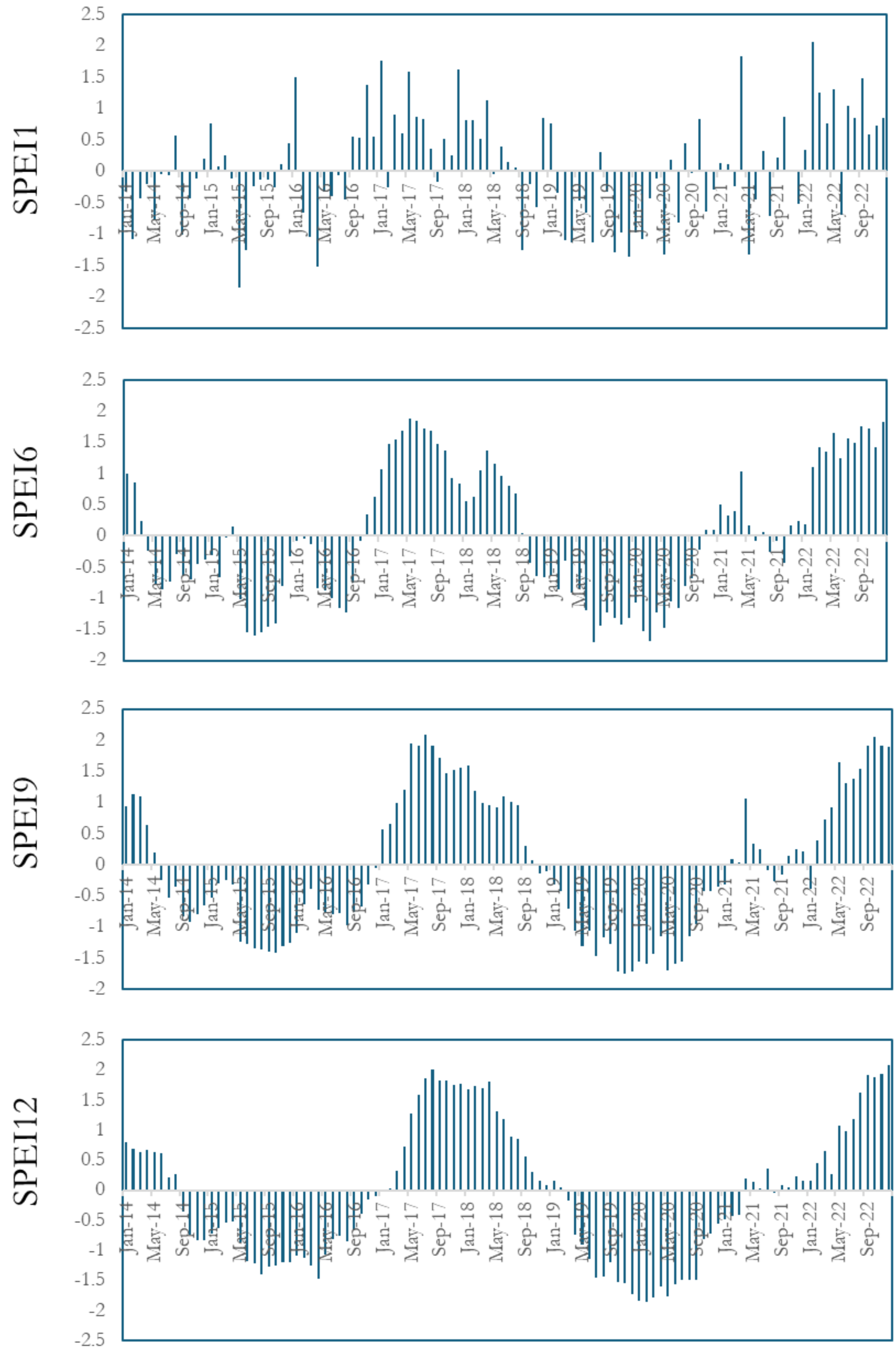

Figure 1: SPEI for Thailand at different time scales

Source: Data from Begueria et al. (2023) SPEIbase v.2.9 (dataset)

The SPEI allows us to consider the directional effects of climate change, where a positive value in the SPEI index indicates wetter-than-normal climate conditions and a negative value implies drier-than-normal climate conditions. In addition, it is possible to classify climate conditions from normal, to moderate, and to exceptionally extreme climate conditions. For example, according to the National Oceanic and Atmospheric Administration (NOAA) classification as shown in Table 2, a SPEI value greater than 1.6 indicates climate conditions that are extremely wet, while SPEI value less than -1.6 indicates climate conditions that are extremely dry. This feature allows us to study the nonlinear impact of climate conditions.

Table 2: Classification of climate conditions according to SPEI value

Climate conditions	SPEI values
Exceptionally wet	SPEI ≥ 2
Extremely wet	1.6 ≤ SPEI < 2
Very wet	1.3 ≤ SPEI < 1.6
Moderately wet	0.8 ≤ SPEI < 1.3
Slightly wet	0.5 ≤ SPEI < 0.8
Near normal	-0.5 ≤ SPEI <0.5
Slightly dry	-0.8 ≤ SPEI < -0.5
Moderately dry	-1.3 ≤ SPEI < -0.8
Very dry	-1.6 ≤ SPEI < -1.3
Extremely dry	-2 ≤ SPEI < -1.6
Exceptionally dry	SPEI < -2

Source: NOAA's National Centres for Environmental Information

According to Figure 1 and classification presented in Table 2, drought seemed to take place around mid2015, end of 2019 and beginning of 2020, while flood seemed to take place in 2017, 2018 and 2022.

3.3 Other control variables

Two main categories of control variables, i.e. financial market risk factors and macroeconomic risk factors, are applied. Details of these two categories of control variables are as follows.

3.3.1 Financial market risk factors

In this paper, we construct the financial market risk factors by considering the six factor models of Fama and French (2018). The factors include market risk premium (MKT), size premium (SMB), value premium (HML), profitability premium (RMW), investment strategy premium (CMA) and momentum premium (UMD). Data on these risk factors for the Thai financial market is obtained from the factor library of the Stock Exchange of Thailand, which was developed by Charoenwong et al (2021). The factor library is computed by using the portfolio formation method based on the risk factors. For example, stock market capitalization is applied to identify the stock with high and low size factors. The size risk premium is computed from the differences between the returns of portfolio of small market capitalization stocks minus those with large market capitalization.

3.3.2 Macroeconomic risk factors

The macroeconomic factors are the market-wide indicators that potentially determine the level of systemic risk. Rahman et al. (2022) show the importance of policy interest rate in determining the systemic risk in the Australian banking sector. According to Jourde and Moreau (2023), the economic sentiment indicator and yield spread between countries with high and low risk in the EU can significantly explain the systemic risk in the European banking sector.

In this paper, for the domestic macroeconomic risk factors, we use the policy interest rate (RP) and term spread (TS), which is computed from the difference between the 5-years government bond yield and the yields of three – month government bond. In addition, we also include the international financial market factor computed from the option trading, i.e. VIX index, as well as the global macroeconomic risk factors, i.e. Economic Policy Uncertainty (EPU), which represent risk condition about economic and government policies observed by the news reports.

After these risk factors are constructed, this paper analyzes the relationship between the climate risk and other risk factors by calculating the correlation coefficients. Then, we investigate the effects of climate risk on systemic risks in the Thai banking sector.

3.4 Effects of climate risks on systemic risks in the Thai banking sector

To investigate the effects of climate risk on financial stability in the Thai banking sector, this paper uses the tail climate risk as the factors that influence the systemic risks in banking sector. The ΔCoVaRs for each individual banks are applied as the dependent variable as a proxy of systemic risk. The change in Value-at-Risk (ΔVaR) of BMG factor are used to measure the tail effect of transition risk. For the physical risk, the SPEI is used as a proxy. To represent the tail risk, we create the dummy variables. The SPEI values that exceed 1.6 or below -1.6 indicate the significant level of risks for flood and drought, respectively; the SPEI values that exceed 2.0 and below -2.0 indicate the extreme level of flood and drought risk, respectively. ΔVaR for financial market risk factors, macroeconomic risk factors and global financial market risk factors are applied as control variables. The panel regression with fixed effect model is applied. We control for cross-sectional heteroscedasticity and contemporaneous correlation in computing robust standard errors. First, we consider the model with traditional risk factors. Model 1.1 use the change in VaR of the long and short portfolio of the six-factor model (Fama & French, 2015). Model 1.2 used the domestic and global macroeconomics and financial market risk factors as determinant factors. Finally, we combined both ΔVaR and macro-finance risk factors in model 1.3.

4. Findings

4.1 Measures of systemic risk among Thai financial institutions

First, we consider the common variation in the tail risk, which is the measure for systemic risk among the Thai financial institutions. We compute the 1-month 95% Value-at-Risk, i.e. the negative return that is not exceed within a month with 95% probability, for each Thai commercial bank. We then compute the Conditional VaR (CoVAR) indicator, which represents the contribution of each financial institution to the financial market sector's tail risk or a proxy for systemic risk. Figure 2 show the plot of ΔCoVar for the 11 Thai commercial banks.

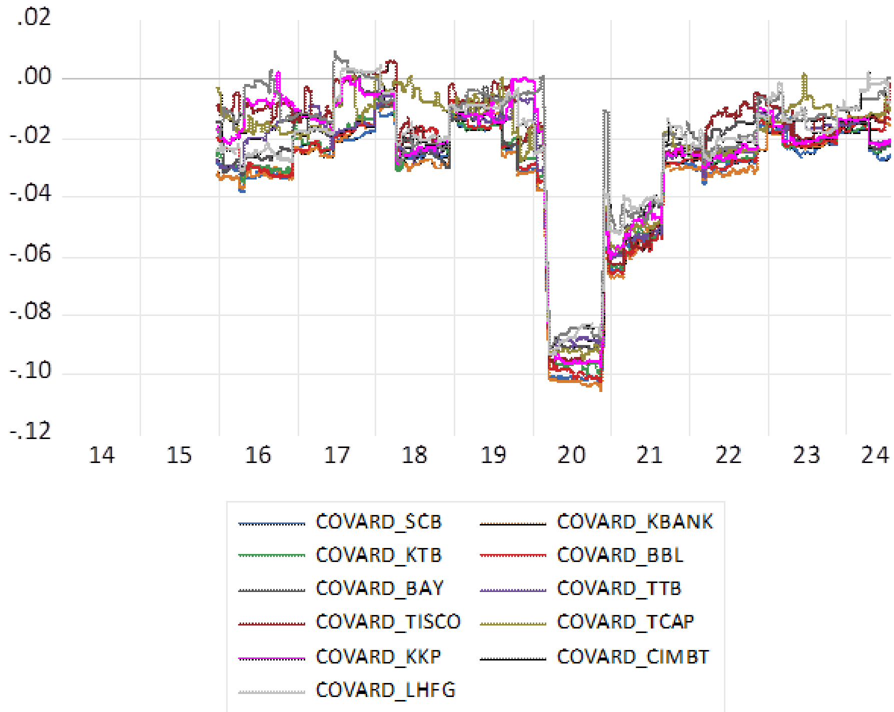

Figure 2: ΔCoVar for the Thai commercial banks

The figure illustrates the dynamics of systemic risk contributions (ΔCoVar) for Thai commercial banks from 2014 to 2024, providing insights into how individual banks' financial distress may affect the broader financial system. A significant decline in ΔCoVar values is observed around 2020, coinciding with the onset of the COVID-19 pandemic. This sharp drop reflects an increase in systemic risk contributions during this period of heightened financial instability.

The trajectories of ΔCoVar across banks exhibit a high degree of co-movement, underscoring the interconnectedness of Thai commercial banks and their collective vulnerability to negative shocks. Following the sharp decline in 2020, the ΔCoVar values show a gradual recovery, indicating a reduction in systemic risk contributions and a stabilization of financial conditions in the years that follow. This trend highlights the capacity of the banking system to recover from significant periods of financial stress. By examining these temporal patterns, the figure emphasizes the importance of tracking systemic risk contributions over time and highlights the challenges posed by episodes of financial turbulence.

4.2 Measures of climate risk factors

To capture the transition risk factor, the long and short portfolio for the BMG factor is constructed and shown in Figure 3.

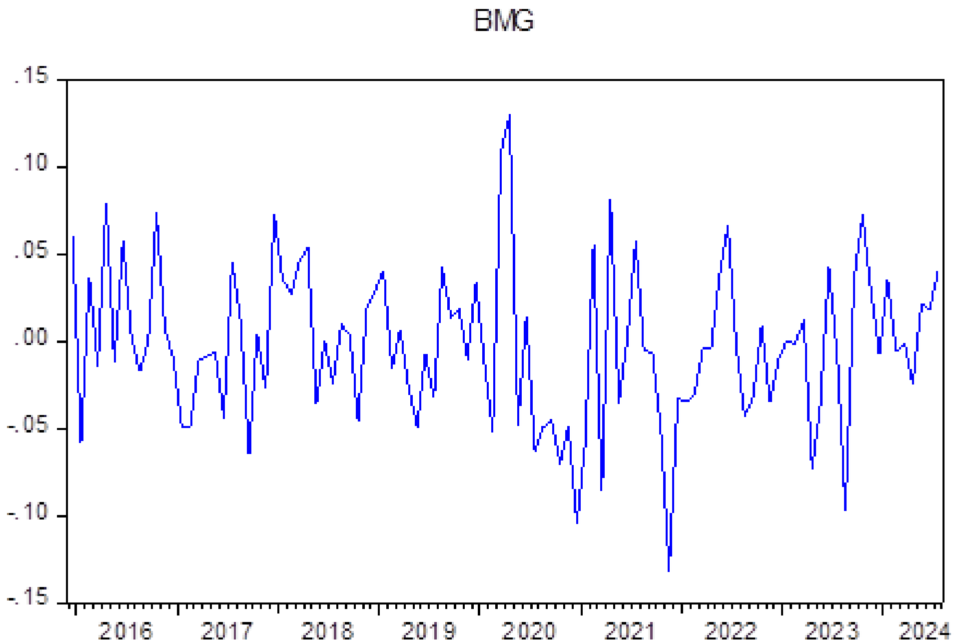

Figure 3: Portfolio construction for BMG factor

Next, we compute the Value-at-Risk (VaR) of the long and short portfolio. The factor VaR from transition risk factors (BMG) are used to measure impacts of transition risk on systemic risk. The change in VaR from the previous level (ΔVaR) reflect the dynamics of tail transition risk. "An increase in tail climate risks may be resulted from a higher risk of correction in GHG intensive stock or an increase in probability of outperformance in low emitter, which is likely to occur in the event of unexpected climate shocks" (Jourde and Moreau, 2024).

For the physical risk factors, Figure 4 displays the SPEI during our study period, along with the critical thresholds of -2.0, -1.5, 1.5, and 2.0. Figure 4 indicates that extreme wet conditions occurred in August 2017 and December 2022. There are no extreme drought conditions within our sample. Moderate drought conditions were observed from December 2019 to May 2020. Additionally, there are two episodes of moderate wet conditions. The first occurred from July 2017 to April 2018, and the second took place between August 2022 and December 2022.

Figure 4: SPEI index for Thailand

Source: Data from Begueria et al. (2023) SPEIbase v.2.9 (dataset)

4.3 Other control variables

Table 3 contains the descriptive statistics for the transition risk factors, along with the premiums from other risk factors, which will be used as the control variables. The results from Table 3 show that momentum risk has the strongest premium among all risk factors, followed by investment strategy risk, market risk and value premiums. In terms of volatility, which is measured by the standard deviation, transition risk, market risk and momentum risk exhibit the highest fluctuation.

Table 3: Descriptive statistics for Fama-French six factors asset pricing models and transition risk factors

	BMG	MKT	SMB	HML	CMA	RMW	UMD
Mean	-0.003	0.003	0.000	0.003	0.005	0.001	0.009
Median	-0.005	0.003	-0.003	0.002	0.002	0.001	0.009
Maximum	0.130	0.180	0.114	0.058	0.120	0.053	0.099
Minimum	-0.132	-0.153	-0.096	-0.058	-0.104	-0.037	-0.175
Std. Dev.	0.046	0.044	0.028	0.025	0.028	0.020	0.041

Remark: BMG – Brown minus Green, MKT – market risk premium, SMB – size premium, HML – value premium, CMA – investment strategy risk premium, RMW – profitability premium, UMD – momentum risk premium

Next, we compute the Value-at-Risk (VaR) of the long and short portfolio. The VaR of the other risk factors among with the BMG factor are shown in Figure 5.

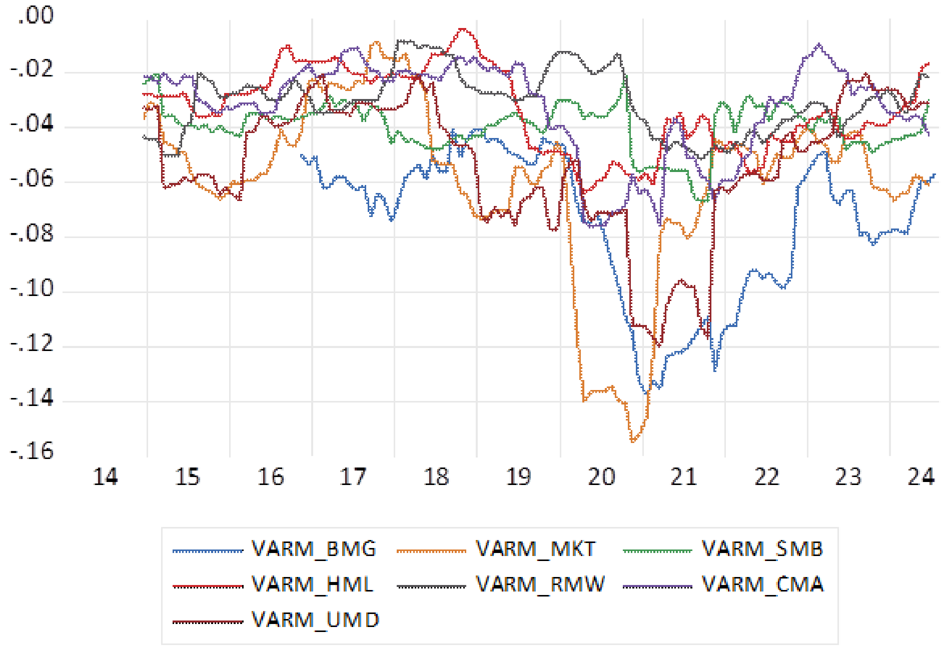

Figure 5: Value-at-Risk (VaR) of the long and short portfolio

According to Figure 5, the market risk is the most sensitive risk factors in the equity market, followed by the BMG factor. Even though, the VaR has increased simultaneously during the Covid-19 pandemic in 2020, the size and timing of change in risk are not the same. For example, the tail risk of market risk factor increased quickly when the Covid-19 pandemic started in the first and second quarters of 2020, while the tail risk of the BMG factor increased during the later period. The tail risk of the BMG factor was still high during 2022 and 2024, which is consistent with the trend of climate risk awareness and adoption of climate-related measures in the developed countries (e.g. the Cross Border Adjustment Mechanism (CBAM) in the European Union (EU) EU's tool to put a fair price on the carbon emitted during the production of carbon intensive goods that are entering the EU, and to encourage cleaner industrial production in non-EU countries[3]) which affect the listed companies in SET that have exposure in those countries.

The macroeconomic and global financial market risk factors, namely the policy interest rate (RP), term spread (TS), VIX index (VIX) and Economic Policy Uncertainty (EPU), are shown in Figure 6.

Next, we analyze the relationship between the climate risk and other risk factors. The correlation coefficients are shown in Tables 4 as follows. According to Table 4, the correlation among financial market risk factors is usually lower than 0.5 with the exception of correlation between market risk and momentum risk that has correlation coefficient equal to -0.511. The correlation between the transition risk factor and other factor is less than 0.2. For physical risk, the correlation between SPEI and other factor is the highest in case of correlation with term spread (0.703) and value factor (HML) (0.254). The correlation between SPEI and other factors is less than 0.2.

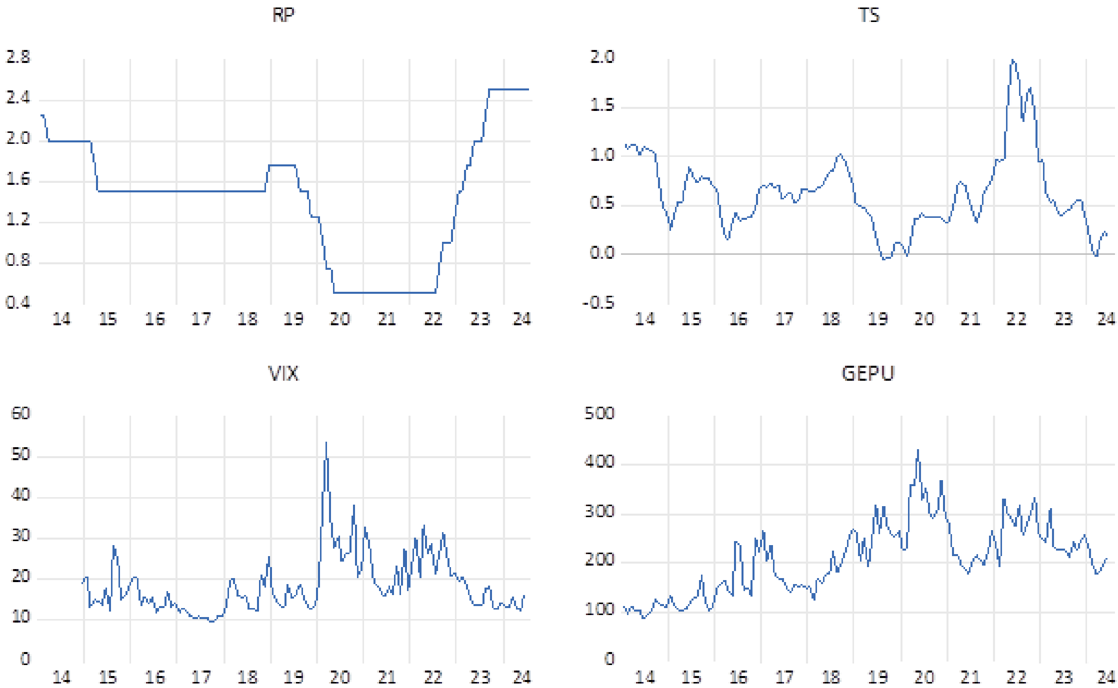

Figure 6: Plots of macroeconomic and global financial market risk factors

Overall, we found that the financial market and macroeconomics risk factors are generally not high. These results highlight the importance of incorporating climate risk to explain systemic risk in Thailand, as it could offer

[3] Source: https://taxation-customs.ec.europa.eu/carbon-border-adjustment-mechanism_en

additional explanatory power beyond traditional factors. The empirical evidence is presented and discussed below.

Table 4: Correlation coefficient of macroeconomic risk factors and financial market risk factors

	SPEI12	BMG	MKT	SMB	HML	RMW	CMA	UMD	RP	TS	VIX	EPU
SPEI12	1	0.014	0.079	-0.239	0.227	-0.112	0.118	-0.002	0.104	0.667	-0.267	-0.333
BMG	0.014	1	-0.046	-0.096	-0.127	0.012	-0.181	-0.020	0.199	-0.016	-0.110	0.060
MKT	0.079	-0.046	1	-0.037	0.116	-0.123	-0.276	-0.511	-0.033	-0.014	-0.612	-0.072
SMB	-0.239	-0.096	-0.037	1	-0.169	0.138	-0.189	0.109	-0.336	-0.070	0.052	-0.031
HML	0.227	-0.127	0.116	-0.169	1	-0.486	0.259	-0.095	0.047	0.165	-0.026	-0.178
RMW	-0.112	0.012	-0.123	0.138	-0.486	1	-0.136	0.053	0.130	-0.209	0.031	-0.033
CMA	0.118	-0.181	-0.276	-0.189	0.259	-0.136	1	0.326	-0.147	0.154	0.185	-0.028
UMD	-0.002	-0.020	-0.511	0.109	-0.095	0.053	0.326	1.000	0.041	-0.114	0.431	-0.002
RP	0.104	0.199	-0.033	-0.336	0.047	0.130	-0.147	0.041	1	-0.248	0.016	0.033
TS	0.667	-0.016	-0.014	-0.070	0.165	-0.209	0.154	-0.114	-0.248	1	-0.058	0.012
VIX	-0.267	-0.110	-0.612	0.052	-0.026	0.031	0.185	0.431	0.016	-0.058	1	-0.148
EPU	-0.333	0.060	-0.072	-0.031	-0.178	-0.033	-0.028	-0.001	0.033	0.012	-0.148	1

4.4 Effects of climate risk on systemic risks in the Thai banking sector

This subsection discusses the effects of climate risk on systemic risk in the Thai banking sector. Three models are considered to find different determinant factors of systemic risks captured by D(CoVAR). Model 1.1 uses the change in VaR (ΔVaR) of the long and short portfolio of the six-factor model (Fama & French, 2015). Model 1.2 uses the domestic and global macroeconomics and financial market risk factors as determinant factors. Model 1.3 combines both ΔVaR and macro-finance risk factors. The regression results are show in Table 5.

Table 5 Regressions on D(CoVaR) with Fama-French 6-factor model (model 1.1) and Macroeconomic risk factor (model 1.2)

Dependent variable D(CoVaR)	Model 1.1	Model 1.2	Model 1.3
D(VARM_MKT)	3.4220		3.290
	(5.738)		(3.169)
D(VARM_SMB)	2.016		0.502
	(8.919)		(5.523)
D(VARM_HML)	-7.365		-21.809**
	(10.400)		(7.039)
D(VARM_RMW)	38.589**		14.036
	(13.900)		(8.098)
D(VARM_CMA)	3.844		1.658
	(9.956)		(5.796)
D(VARM_UMD)	4.261		4.418
	(4.969)		(3.688)
RP		0.431***	0.439***
		(0.061)	(0.064)
TS		0.442***	0.473***
		(0.083)	(0.087)
LOG(VIX)		-0.260*	-0.256*
		(0.141)	(0.136)
LOG(EPU)		-0.501**	-0.473**
		(0.178)	(0.173)
C	-0.585***	2.057**	-1.864**
	(0.048)	0.727	(0.705)
Adjust-Rsquared	0.117	0.617	0.672

MKT – market risk premium, SMB – size premium, HML – value premium, RMW – profitability premium, CMA – investment strategy risk premium, UMD – momentum risk premium, RP – monetary policy interest rate (repurchase rate), TS – term spread (5 year bond yield – 3 month bond yield, VIX is US volatility index, EPU – global economic policy uncertainty index.

According to Table 5, the results from model 1.1 show that the ΔVaR of traditional market risk factors have limited ability to explain systemic risk in the Thai banking sector. Only ΔVaR of profitability risk factor (RMW) is statistically significant. Surprisingly, the market risk (MKT), which is the key risk factors in financial theory is not statistically significant. Moreover, the adjusted-R-squared is 0.117, which exhibit the omission of key important factors in the model. In model 1.2, the adjusted R-squared equals to 0.617. The regression results under model 1.2 shows that the macroeconomic and global financial market risk factor are the key elements determining the systemic risk in Thai banking sector. This result is not surprising as the banking sector is sensitive to the policy interest rate and yield spread. The global risk factors, such as VIX and global economic policy uncertainty index (EPU), are statistically significant at 10 and 5 percent level, respectively. Lastly, model 1.3 shows that by controlling the risk from macroeconomic factors, ΔVaR from valuer risk (HML) become statistically significant. All macroeconomic and global risk factors still exhibit significant results. Adjusted R-squared of model 1.3 increases to 0.672. These results provide the robustness of our baseline model in explaining the systemic risk in the Thai banking sector.

Next, we consider the models with climate risk factors as the additional explanatory factors for determining systemic risk in the Thai banking sector. We include ΔVaR for transition risk (BMG) and SPEI index for physical risk. Moreover, as discussed in previous section the value of SPEI provides the risk in both size of positive and negative number, with positive and negative numbers reflecting the wet and dry conditions, respectively. To control for this issue, we employ the absolute value and squared value of SPEI index in model 2.1 and 2.2, respectively. The 12-month SPEI or SPEI12 is considered in the regression. Table 6 presents the regression results.

According to Table 6, the results show that ΔVaR for BMG factor is statistically significant at 5 percent significant level. The adjusted R-squared of models 2.1 and 2.2 are 0.742 and 0.738, respectively. In addition, the physical risk factor SPEI is statistically significant at 5 percent level in both models 2.1 and 2.2, where model 2.1 considers the absolute value of SPEI12 and model 2.2 considers the squared value of SPEI12.

Next, in model 2.3, we investigate the asymmetric effect of physical risk during the wet and dry conditions. We use the dummy variable with value of 1 when SPEI exceeds 0 and 0 when SPEI is equal to/ or less than zero to separate the positive and negative impact of physical risk. The positive SPEI (SPEI+) is computed from the product between the dummy variables and

SPEI index (SPEI+ = Dummy*SPEI), while the negative SPEI (SPEI-) is calculated from the case of negative value in SPEI (SPEI- = (1-Dummy)*SPEI). As shown in Table 6, in model 2.3, both SPEI+ and SPEI- are not statistically significant at 10 percent level.

Last but not least, we consider the tail of physical risk by using dummy variable for moderate and severe values of dry and wet conditions. We include the dummy variable, SPEI>1.6 equal to 1 when SPEI is more than 1.6. We also use these dummy variables for the value of SPEI >2, SPEI < -1.6. As discuss in last section, there are no period with the extreme drought condition (SPEI <-2) in our sample thus the dummy SPEI < -2 is not included in the regression. These dummy variables provide the way to determine the tail physical risk. The results from model 2.4 in Table 6 show that the dummy variables are significantly in case of SPEI > 1.6, which show the sensitivity of systemic risk to the moderate level of flood in Thailand. The dummy variable for tail physical risk, i.e., SPEI>2, is not statistically significant. The adjusted R-squared number for models 2.4 is equal to 0.740. The results from transition risk factor are consistnent in all models. The increase in the transition risk (ΔVAR(BMG)) leads to an increased sensitivity of systemic risk in the Thai banking sector. For the other variables, the macroeconomic risk factors, i.e. the monetary policy interest rate (RP), term spread (TS) and global economic policy uncertainty (EPU) are statistically significant. The change in Value-at-Risk of the market risk factor is also significant at 5 percent level in model 2.4. These results confirm the role of macroeconomic and international financial market risk factors in determining the systemic risk in the Thai banking sector. The results also show that including tail of both transition and physical risk provide additional explanatory power for systemic risk in the Thai banking sector.

Table 6 Regressions on D(CoVaR) with climate risks factors

	Model 2.1		**Model 2.2**		**Model 2.3**		**Model 2.4**
|SPEI|	-0.114**	SPEI^2	-0.049**	SPEI+	-0.078	SPEI > 2	0.121
	(0.043)		(0.022)		(0.047)		(0.106)
						SPEI > 1.6	-0.141*
							(0.070)
				SPEI-	0.196	SPEI < -1.6	0.225
					(0.115)		(0.192)
D(VARM_BMG)	10.818**		11.364**		10.314**		11.680**
	(4.184)		(4.292)		(3.988)		(4.467)
D(VARM_MKT)	3.919		4.102		3.559		7.014*
	(3.229)		(3.309)		(3.066)		(3.508)
D(VARM_SMB)	-5.337		-5.122		-5.264		-5.024
	(6.037)		(6.126)		(6.089)		(6.011)
D(VARM_HML)	-17.847*		-17.991*		-15.181*		-22.204**
	(8.346)		(8.375)		(8.249)		(8.547)
D(VARM_RMW)	25.516**		24.146**		27.321**		18.920*
	(8.909)		(8.983)		(9.200)		(8.777)
D(VARM_CMA)	-3.241		-3.482		-3.721		-3.341
	(6.393)		(6.503)		(6.319)		(6.182)
D(VARM_UMD)	8.390*		8.606*		8.839**		7.147*
	(3.816)		(3.895)		(3.926)		(3.890)
RP	0.687***		0.680***		0.688***		0.661***
	(0.084)		(0.082)		(0.083)		(0.085)
TS	0.408***		0.407***		0.294*		0.499***

	Model 2.1		Model 2.2		Model 2.3			Model 2.4
	(0.091)		(0.090)		(0.152)			(0.097)
LN(VIX)	-0.076		=0.078		-0.056*			-0.107
	(0.148)		(0.148)		(0.201)			(0.145)
LN(EPU)	-0.383		-0.398**		-0.236			-0.520**
	(0.171)		(0.174)		(0.224)			(0.207)
C	0.7690		0.813		-0.013			1.459
	(0.724)		(0.734)		(1.067)			(0.889)
Adjusted-Rsquared	0.742		0.738		0.744			0.740

MKT – market risk premium, SMB – size premium, HML – value premium, RMW – Profitability premium, CMA – investment strategy risk premium, UMD – momentum risk premium

RP – monetary policy interest rate (repurchase rate), TS – term spread (5 year bond yield – 3 month bond yield, VIX is US volatility index, GEPU – global economic policy uncertainty index.

Transition risk BMG – Brown industries minus Green industries, SPEI - Standardized Precipitation Evapotranspiration Index

5. Concluding remarks

As climate change can profoundly affect asset prices and financial stability (Carney, 2015), the impact of climate risks on systemic risk has become one of the central concerns in the financial community. This paper investigates the effects of climate risks on systemic risk in the Thai banking sector. Both types of climate risks—transition and physical risks—are considered.

The transition risk factor is constructed using the financial market data based on the empirical asset pricing model of Fama and French. Specifically, the risk premium of brown industries relative to green industries is calculated using the long and short portfolio. This is denoted by Brown minus Green (BMG). The physical risk is captured through the Standardized Precipitation Evapotranspiration Index (SPEI). Systemic risk at the bank level is measured using the conditional value-at-risk (CoVaR), based on trading data from the Stock Exchange of Thailand.

To examine the effects of climate risks on systemic risk, panel regressions are conducted. The explanatory variables in the regressions include the Fama-French (2015) risk factors, macroeconomic and global financial market risk factors, as well as the climate risk factors—both BMG and SPEI. Our empirical results show that macroeconomic risk factors, such as the monetary policy interest rate (RP) and term spread (TS), as well as global financial market risk factors, such as global economic policy uncertainty (EPU), are statistically significant. Furthermore, the transition risk, measured by the BMG factor, significantly impacts systemic risk among Thai banks. For physical risk, bank portfolios are particularly exposed to moderate wet conditions (i.e., flood risks). These findings confirm the role of macroeconomic and international financial market risk factors in shaping systemic risk in the Thai banking sector. Additionally, incorporating the tails of both transition and physical risks provides further explanatory power for systemic risk in Thailand's banking sector.

As the impacts of climate risks on financial stability become an increasing concern for central banks and financial supervisors, the findings of this paper can inform policymakers in Thailand about the extent to which climate risks affect systemic risk and the degree of risk externalities that individual banks impose on the financial system. This, in turn, has implications for financial stability. As Thailand and many other countries transition toward a low-carbon economy, banks and financial institutions with cleaner investment and lending portfolios are likely to be less exposed to transition risks.

To manage the physical risks facing banks, strategies can be implemented by both the banks themselves and central banks or regulatory bodies. For banks, these strategies may involve risk identification, risk assessment, and the development of risk reduction measures.

First, in terms of risk identification, banks and financial institutions could conduct sector and location analyses using portfolio exposure and climate hazard data. These analyses help identify vulnerable areas and climate hotspots that require focused attention. Second, for risk assessment, three components of risk should be considered: hazard, vulnerability, and exposure. Climate hazard assessment involves identifying extreme weather events, such as floods and droughts, that affect specific regions. Vulnerability assessment measures the sensitivity of businesses to these hazards in terms of the severity and frequency of such events. Finally, exposure assessment evaluates the extent to which assets, workforces, loan portfolios, and other resources are affected by climate hazards.

Examples of physical risk reduction strategies for banks include using credit protection insurance, adjusting pricing in highly exposed areas, adopting climate risk protection insurance, shifting the mix of customer segments, or offering higher discounts on low-risk assets (Goossens et al., 2023).

Beyond managing risks, banks can also create competitive advantages and generate value by developing innovative financing products and solutions for their clients. For example, they could foster and finance the adoption of climate adaptation measures. While physical climate risks pose significant threats to banks, they also present unique opportunities for innovation within the banking sector. Banks that act early and take appropriate steps can not only enhance their financial stability but also help mitigate negative externalities on systemic risks. Commercial banks in Thailand, in particular, can leverage the indicators presented in this paper to conduct climate stress tests and develop strategies for managing these risks more effectively.

To manage transition risks, it is imperative for banks to assess the risks within their loan portfolios and identify mitigating solutions (Park-Minc, 2022). Banks should adopt appropriate valuation models or metrics to evaluate the financial risks associated with their carbon-intensive assets. The process of integrating transition risk management involves a series of steps: assessment, quantification of financial impact, integration, and reporting. This process is complex and requires banks to first build internal capacity, utilize tailored technical tools, and establish dedicated task forces to implement the steps effectively. Even when a third party is employed to conduct the entire process, it is highly recommended that banks maintain internal oversight to ensure accuracy and reliability. The complete transition risk integration framework typically includes seven steps, from initial assessment to final reporting.

Central banks and financial sector supervisors, as the guardians of financial stability, also have crucial roles in mitigating the impacts of climate risks on the financial system. They must ensure that climate-related risks are adequately assessed and incorporated into supervisory processes (Adrian, 2023). For instance, physical risks, such as increasingly frequent and severe natural disasters, and transition risks, such as stranded assets during the shift to a low-carbon economy, must be integrated into risk assessments and prudential frameworks. This approach ensures that financial institutions are resilient to climate-related shocks.

To support banks in accurately measuring these risks, central banks and financial supervisors need to enhance their stress-testing frameworks. These frameworks should account for the transmission channels through which climate risks exacerbate and propagate risks within the financial sector. Additionally, addressing data gaps in supervisory reporting and financial disclosures is a prerequisite for effective climate-related risk supervision.

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