CLIMATE RISK AND FINANCIAL STABILITY: A SYSTEMIC RISK PERSPECTIVE FROM THAILAND

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Joint NSD-INSE-PIER Macroeconomics Research Workshop

26 September 2025

Motivation

- **Climate change poses significant risks to financial stability**, especially in emerging markets.
  - Financial systems face both direct impacts (asset devaluation, credit defaults) and indirect impacts (liquidity spirals, contagion) from climate change.
  - Climate risks propagate through both physical channels (floods, droughts, extreme weather) and transition channels (carbon pricing, stranded assets, policy shocks).
- **Climate risks can amplify into systemic risks**, i.e. risks capable of disrupting the functioning of the entire financial systems.
- **Thailand is highly exposed and vulnerable** to the adverse impacts of climate shocks given limited fiscal space and institutional readiness.
- **Urgent need to integrate climate risks into systemic risk frameworks** to inform stress testing and regulatory policy.

This Paper

- This paper examines **the systemic implications of climate risks for financial stability** in the the case of Thailand.
- The key question to be answered in this paper:
  - How do transition and physical climate risks affect systemic risk in Thailand's banking sector?
- Highlighted measures used in the analysis:
  - Systemic risk at the bank level is measured using the conditional value-at-risk (CoVaR).
  - Transition risk is captured by the risk premium for brown vs. green industries using a long-short portfolio (BMG).
  - Physical risk is measured by the Standardized Precipitation Evapotranspiration Index (SPEI).
- Panel regressions, controlling for risk factors and macroeconomic variables, are used to quantify the impact of climate risks on systemic risk.

Related Literature

Our work is related to several strands of literature.

- **Impacts of climate risks on financial stability** (Carney, 2015; Dietz et al., 2016; Battiston et al., 2017; Li et al., 2021; Roncoroni et al., 2021).
  - Battiston et al. (2017) highlight the importance of climate stress-testing for financial stability.
  - Roncoroni et al. (2021) 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.
- **Systemic risk and financial linkages:**
  - Adrian and Brunnermeier (2008) proposed using stock market data to calculate the **conditional value-at-risk (CoVaR) to measure the degree of "risk externalities"** that an individual institution imposes on the broader financial system.
  - Roengpitya and Rungcharoenkitkul (2011) **applied the concept of CoVaR to investigate Thai banking sector**. Their findings revealed that individual banks imposed additional risk on the overall system.
  - Jourde and Moreau (2023) utilized a market-based framework to **examine systemic climate risks in the financial sector** using Adrian and Brunnermeier (2016).

Empirical Method

(1) Panel data regression

Dependent variables: ΔCoVaR: bank level; time-series data

Climate risk variables : $\Delta VaR_{BMG,t}$ (transition risk) and SPEI (physical risk)

Control variables:

- Financial market risk factors ($\Delta VaR_{j,t}$)
- Macroeconomic & international market risk ($\mathbf{X}_t$)
- Fixed effect (a_i)

$$\Delta CoVar_{i,t} = \alpha + \delta|SPEI_t| + \gamma\Delta VaR_{BMG,t} + \beta_j\Delta VaR_{j,t} + \gamma_k X_{k,t} + a_i + u_{i,t}$$

$$\Delta CoVar_{i,t} = \alpha + \delta SPEI_t^2 + \gamma\Delta VaR_{BMG,t} + \beta_j\Delta VaR_{j,t} + \gamma_k X_{k,t} + a_i + u_{i,t}$$

$$\Delta CoVar_{i,t} = \alpha + \delta^+(SPEI > 1.6)_t + \delta^-(SPEI < -1.6)_t + \gamma\Delta VaR_{BMG,t} + \beta_j\Delta VaR_{j,t} + \gamma_k X_{k,t} + a_i + u_{i,t}$$

Empirical Method

(2) Systemic risk measurement

- Value at Risk for bank i and for all banks are computed from the (rolling) standard deviation of stock returns on bank portfolio (obtained from stock market trading data) to identify the potential loss that occur in the bad situation (tail risk of portfolio return's distribution)

$$\mathrm{VaR(i)} = \mathrm{Z} * \sigma(i)$$

- CoVaR (Conditional Value at Risk) measures systemic risk by capturing the risk of the financial system conditional on a particular institution being in distress.
- CoVaR of the financial system at the q% quantile conditional on institution i's distress is obtained by estimating the following quantile regression model:

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

Empirical Method

(2) Systemic risk measurement

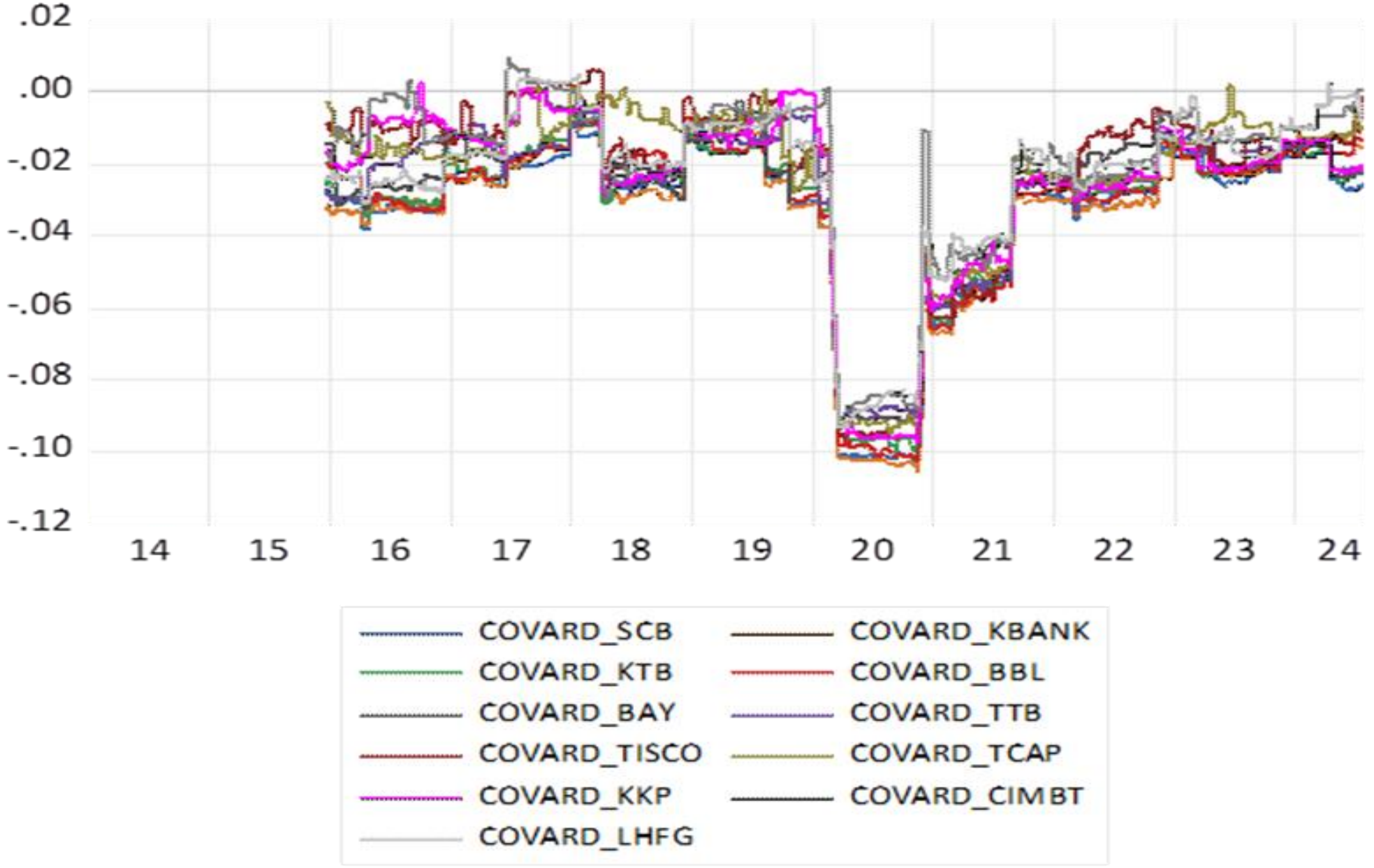
- ΔCoVaR is defined as the difference between the CoVaR conditional on institution i being in distress and the CoVaR conditional on institution i being in its median state:

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

- To compute ΔCoVaR, we calculate the the difference between the CoVaR when institution i is in distress and the CoVaR when the institutioin i is in its median state:

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

ΔCoVar for the Thai commercial banks

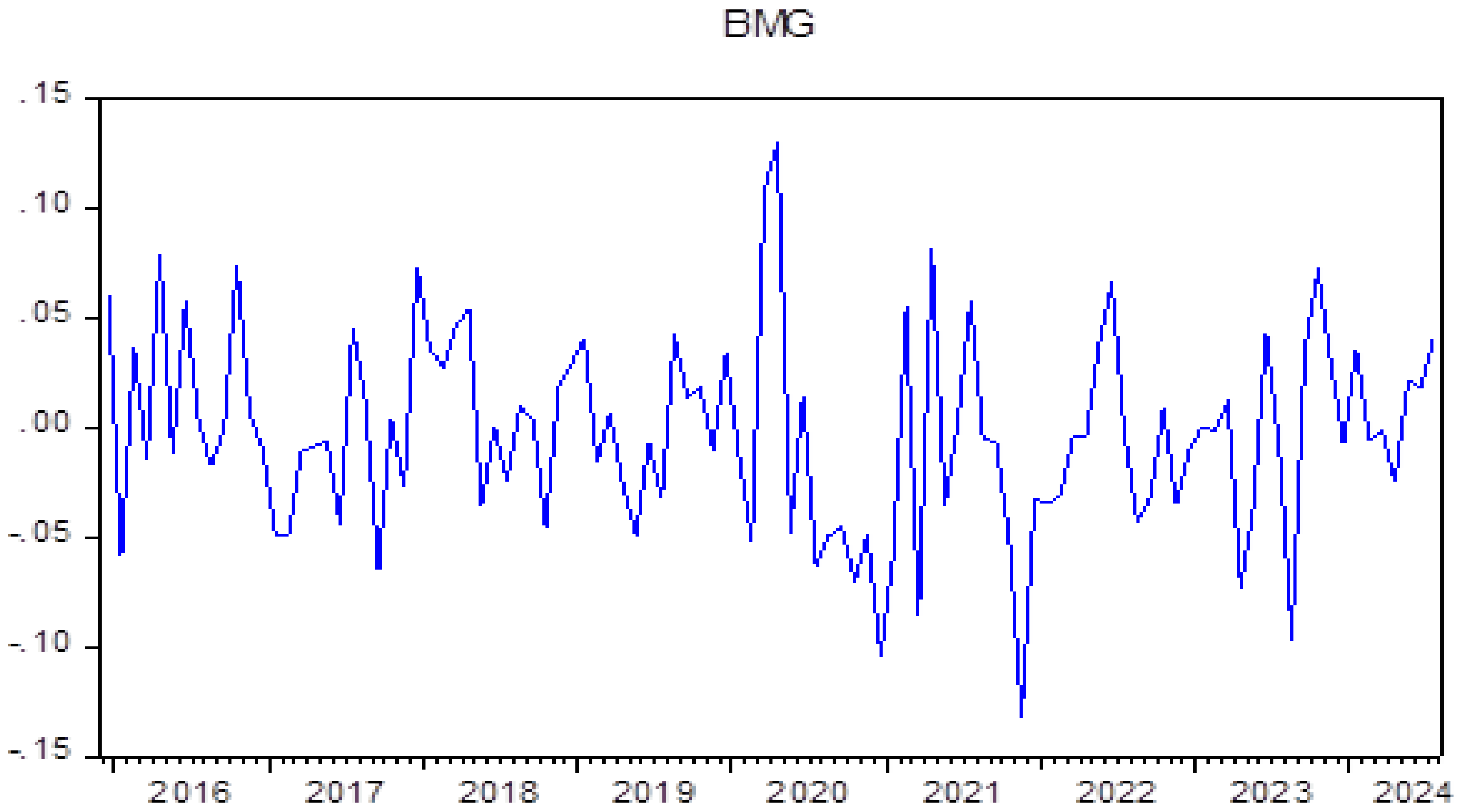


Empirical Method

(3) Climate Risk Factors - Transition risks

- The transition risk factor is constructed using the financial market data based on the empirical asset pricing model of Fama and French (1993, 2015).
- 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.
- The "Brown minus Green (BMG)" captures the returns of the transition risk factor.
- To estimate BMG factor, the following process is applied:
  - Retrieve the carbon intensity of listed companies, focusing on the top 300 firms by market capitalization.
  - Rank these companies by their GHG emission intensity per unit of sales (proxy for carbon efficiency)
  - Classify stocks into quintiles, with the first quintile representing brown stocks and bottom quintile representing green stocks.
  - BMG factor is calculated as the difference in returns between the brown and green portfolios.

BMG Factor

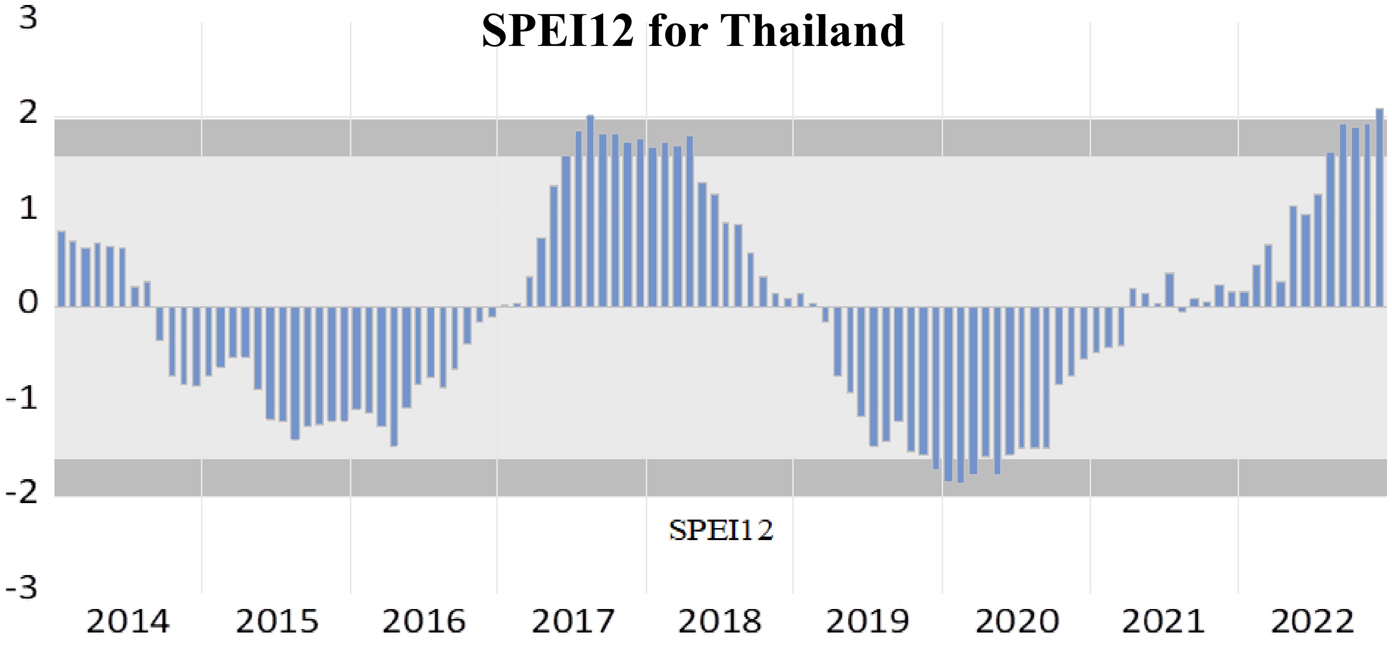

BMG
.15
.10
.05
.00
-.05
-.10
-.15
2016
2017
2018
2019
2020
2021
2022
2023
2024

Empirical Method

(4) Climate Risk Factors – Physical risks

- This paper uses the Standardized Precipitation Evapotranspiration Index (SPEI) to capture the physical risk.
- SPEI enables us to quantify flood and drought severity and assessing impacts across different sectors; thus, this has advantage over the use of physical risk scores used in the literature.
- SPEI is calculated using data on precipitation and atmospheric evaporative demand, and it can be calculated at different time scales (1-48 months).
- In this study, the 12-month SPEI or SPEI12 is selected as it reflects the long-term trend and maintains interannual drought changes (Liu et al., 2021).

SPEI index



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

Empirical Method

(5) Control variables

Financial market risk factors

- Market risk premium (MKT)
- Size premium (SMB)
- Value premium (HML)
- Profitability premium (RMW)
- Investment strategy premium (CMA)
- Momentum premium (UMD)

Source: Factor library of the Stock Exchange of Thailand developed by Charoenwong et al (2021)

Macroeconomic risk factor

- Policy interest rate (RP)
- Term spread (TS) : 5-years yield MINUS 3–months yield (Government bond)

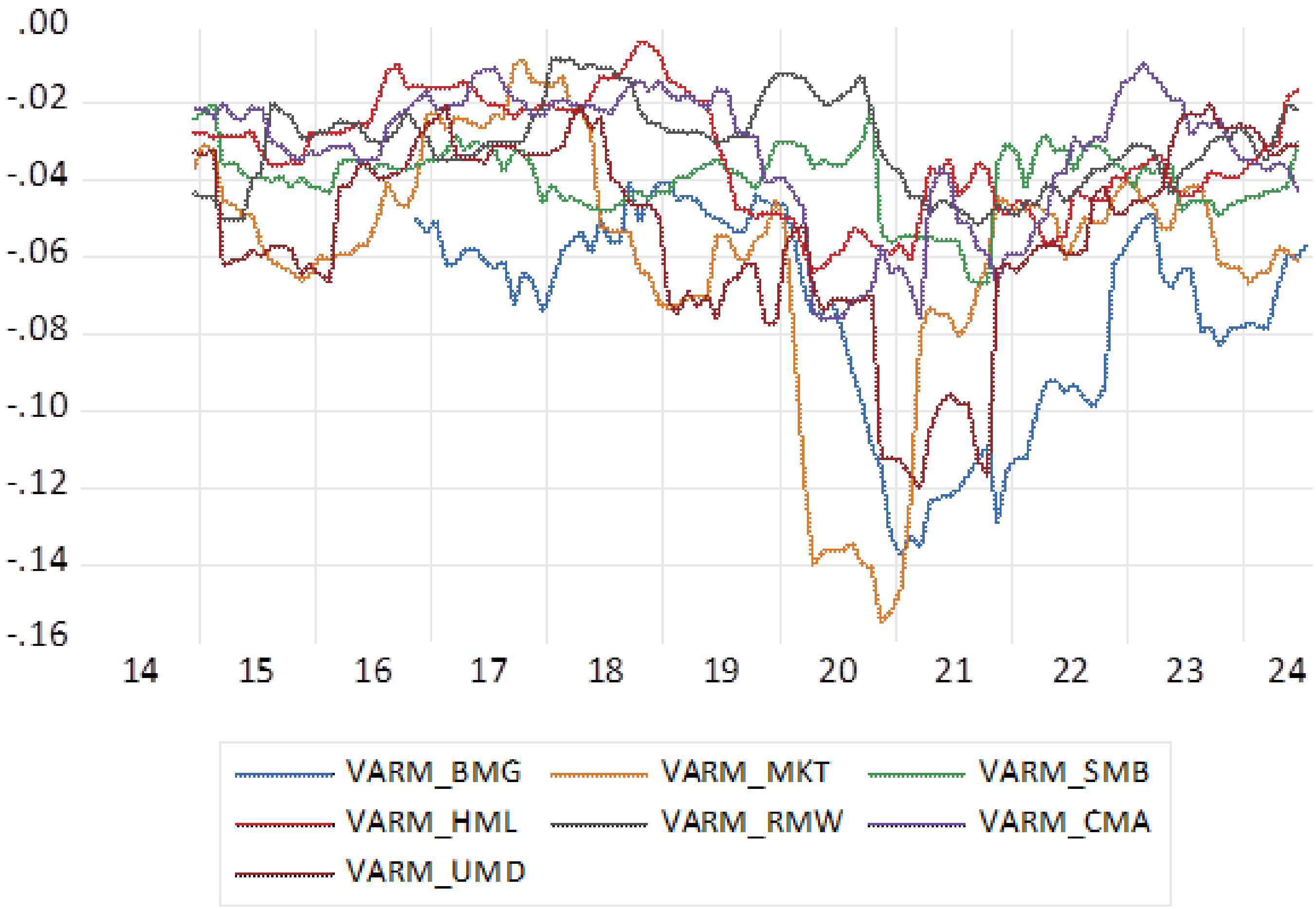
Source: Bank of Thailand

International financial market risk factors

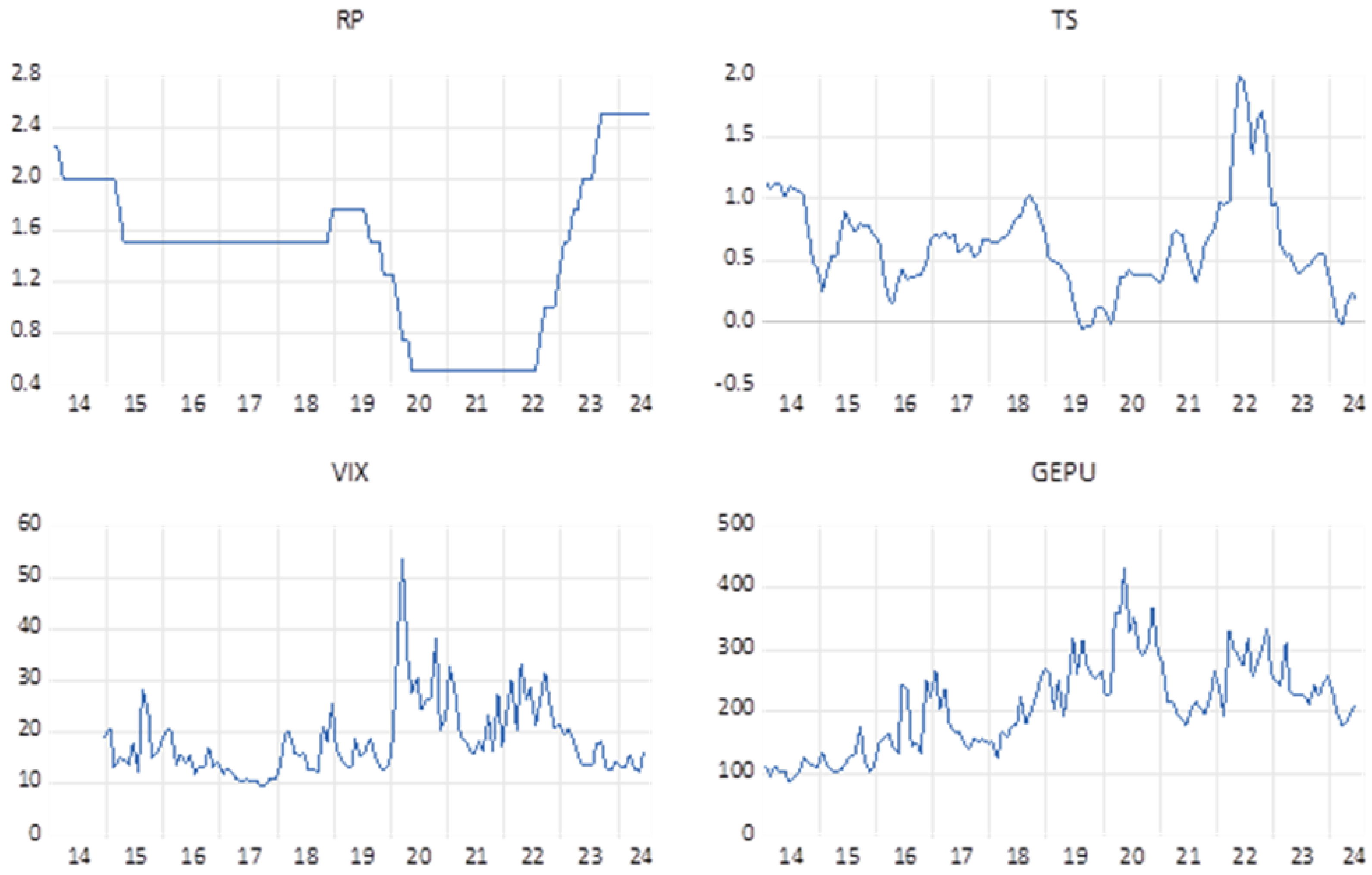
- VIX index - computed from the option trading (fear index) in S&P index (Source: CBOE)
- Global Economic Policy Uncertainty (EPU) – the risk condition about economic and government policies observed by the news reports (average from the major financial markets)

Source: Baker, Bloom & Davis

VaR of the other risk factors



Macroeconomic and global financial market risk factors



Dependent variable D(CoVaR)	Model 1.1	Model 1.2	Model 1.3
D(VARM_MKT)	6.099		7.210**
	(5.897)		(2.743)
D(VARM_SMB)	-3.162		-4.313
	(11.296)		(6.518)
D(VARM_HML)	-11.920		-18.078***
	(11.730)		(8.013)
D(VARM_RMW)	43.703**		21.673**
	(16.005)		(9.232)
D(VARM_CMA)	7.068		0.442
	(9.750)		(4.933)
D(VARM_UMD)	4.895		6.275
	(5.127)		(4.287)
RP		0.624***	0.644***
		(0.096)	(0.098)
TS		0.479***	0.506***
		(0.076)	(0.082)
LOG(VIX)		-0.144	-0.091
		(0.136)	(0.148)
LOG(EPU)		-0.523**	-0.460**
		(0.175)	(0.184)
C	-0.622***	1.626*	1.090
	(0.051)	(0.791)	(0.825.)
Adjusted-R^2	0.143	0.658	0.717
Number of total pool observation	803	803	803

RESULTS

RESULTS

Dependent variable D(CoVaR)		Model 2.1		Model 2.2		Model 2.3
Physical Risk (SPEI)	$\lvert SPEI \rvert$	-0.139**	$SPEI^2$	-0.062**	SPEI > 1.6	-0.152*
		(0.046)		(0.023)		(0.072)
					SPEI < -1.6	0.150
						(0.199)
Transition risk		10.491**		11.157**		11.731**
D(VARM_BMG)		(4.193)		(4.393)		(4.587)
D(VARM_MKT)		5.601*		5.747*		8.276**
		(2.757)		(2.913)		(3.208)
D(VARM_SMB)		-7.145		-6.984		-6.343
		(6.047)		(6.278)		(5.943)
D(VARM_HML)		-18.320**		-18.478**		-22.671**
		(7.496)		(7.715)		(8.160)
D(VARM_RMW)		27.891***		26.520**		20.188**
		(8.433)		(8.741)		(8.702)
D(VARM_CMA)		-3.793		-4.174		-4.065
		(5.189)		(5.303)		(5.153)
D(VARM_UMD)		8.842**		9.159**		7.701*
		(3.876)		(4.046)		(3.893)
RP		0.702***		0.692***		0.651***
		(0.092)		(0.092)		(0.092)
TS		0.479***		0.479***		0.552***
		(0.083)		(0.083)		(0.097)
LN(VIX)		-0.014		-0.019		-0.051
		(0.139)		(0.142)		(0.141)
LN(EPU)		-0.442**		-0.458**		-0.592**
		(0.163)		(0.170)		(0.206)
C		0.862		0.813		1.673
		(0.721)		(0.734)		(0.928)
Adjusted-R^2		0.756		0.753		0.744
Number of total pool observation		803		803		803

Key Findings

- 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. The results provide the indicators for the reliable of our systemic risk variables (ΔCoVaR), which link the standard risk factor in literature.
- The transition risk, measured by the BMG factor, significantly impacts systemic risk among Thai banks.
  - Higher risk premium on transition of carbon emission industry explain common downside tail risk in banking system
  - Lead to the issue of financial stability in bank sector
- For physical risk, bank portfolios are particularly exposed to extremely wet conditions (i.e., flood risks).
  - Major flooding arise from climate change could provide the crucial impacts on financial stability
  - In Thailand, major floods affect not only agriculture business but also manufacturing plants and tourist attractions.

Conclusion

- Thailand is highly exposed to climate hazards, its an economic structure is reliant on climate-sensitive sectors, and Thailand's financial system is increasingly integrated with global capital markets.
- This paper investigates the effects of climate change on financial stability in the Thai banking sector, considering both transition and physical risks.
- Our empirical results show that transition risk—measured by the Brown-minus-Green (BMG) factor—significantly amplifies systemic risk in the Thai banking sector.
- Physical risk also matters, with bank portfolios particularly exposed to extremely wet conditions such as flood risk, while drought risk appears limited due to the sector's relatively low agricultural lending exposure.
- These differentiated effects highlight that transition and physical risks propagate through distinct channels, both of which merit targeted attention in risk management and supervisory frameworks.

Potential policy implications

- **Banks:** To manage transition risks, banks must assess 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.
- **Central banks and financial sector supervisors:** As guardians of financial stability, central banks and regulators have a crucial responsibility in mitigating the impacts of climate risks on the financial system.
    - They must ensure that climate-related risks are not just assessed, but fully incorporated into supervisory processes (Adrian, 2023).
    - Physical risks and transition risks must be integrated into risk assessments and prudential frameworks. This approach ensures that financial institutions are resilient to climate-related shocks.
    - Central banks and financial supervisors must enhance their stress test frameworks to support banks in accurately measuring these risks.