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Asymmetric Effects of Climate Risk on Bank Stock Volatility: The Role of Market Sentiment in Global Systemically Important Banks

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Abstract

This paper examines the asymmetric effects of climate risk on bank stock volatility using data of ten major global banks. Findings are: first, macro-financial uncertainty is the driver of bank stock volatility. Second, a pronounced asymmetry presents in the climate risk-volatility relationship. Third, market sentiment plays a critical role in shaping these effects. Consumer confidence amplifies the volatility impact of transition risk but attenuates the effect of physical risk. Fourth, the covariance between investor sentiment and market volatility amplifies the impact of transition risk variance, while the corresponding interaction with consumer confidence dampens the effect of physical risk variance.

Keywords

Climate Risk, Bank Stock Volatility, Transition Risk, Physical Risk, Market Sentiment

1. Introduction

Climate change poses a growing and multifaceted challenge to the global financial system. As extreme weather events become more frequent and the transition to a low-carbon economy accelerates, financial institutions—particularly global systemically important banks (G-SIBs)—face two distinct but interconnected sources of risk: physical risk arising from climate-related disasters and transition risk arising from policy, technological, and regulatory adjustments [1].

Understanding how these risks affect bank stock volatility is crucial for financial stability, macroprudential policy design, and risk management. Recent work by international regulatory institute, Bank for International Settlements, BIS [2] em-

phasizes that climate-related risks are not merely tail events but structural forces reshaping asset valuations, credit risk, and systemic stability. Banks, as central financial intermediaries, are particularly exposed through their lending portfolios, trading activities, and counterparty networks [3]. Climate shocks can therefore propagate to bank balance sheets via deteriorating collateral values, rising default probabilities, and compressed profitability margins, ultimately affecting equity volatility [4].

Despite the growing literature, an important gap remains: the heterogeneous effects of different climate risk dimensions on bank stock volatility, and the role of market sentiment in shaping these effects. In particular, it is unclear whether transition and physical risks are transmitted to financial markets through similar mechanisms or whether they exhibit fundamentally different dynamics once sentiment conditions are taken into account.

This paper addresses this gap by examining the asymmetric effects of climate risk on bank stock volatility, with a focus on the moderating role of market sentiment in a panel of G-SIBs. Our empirical analysis yields four main findings. First, consistent with established evidence on systematic risk, macro-financial uncertainty—captured by equity market volatility (EMV), VIX, and related indicators—remains a key determinant of bank stock volatility.

Second, we document a clear asymmetry in the impact of climate risk. Transition risk variance increases bank stock volatility, while physical risk variance reduces it. This pattern reflects fundamental differences in risk structure. Transition risk is driven by endogenous policy uncertainty, regulatory ambiguity, and technological disruption, generating Knightian uncertainty that is difficult to hedge or price precisely. In contrast, physical risk is more observable, geographically dispersed, and increasingly internalized through insurance markets, collateral adjustments, and gradual learning.

Third, we show that these effects are strongly state-dependent on sentiment conditions. Consumer confidence amplifies the volatility effects of transition risk but mitigates those of physical risk. This suggests that sentiment influences how investors process different types of climate-related information: during periods of high confidence, markets become more sensitive to structural uncertainty about the transition path, while perceiving physical risks as more manageable and better absorbed by the financial system.

Fourth, we find that the interaction between sentiment-volatility co-movement and climate risk further strengthens these asymmetries. The covariance between investor sentiment and market volatility amplifies the impact of transition risk variance on bank stock volatility, whereas the corresponding interaction with consumer confidence reduces the effect of physical risk variance, especially for those non-U.S. banks.

These findings contribute to literature in several ways. First, we provide systematic evidence of asymmetric climate risk effects on bank stock volatility for G-SIBs, distinguishing between transition and physical risk channels. Second, we

highlight the importance of sentiment as a key amplification and stabilization mechanism in climate risk transmission. Third, we show that macro-financial uncertainty remains a dominant driver of bank volatility even after accounting for climate risk. Finally, we demonstrate that climate risk transmission is inherently state-dependent, with distinct implications across different sentiment regimes.

The remainder of the paper is organized as follows. Section 2 reviews literature review. Section 3 presents testable hypotheses and research methodology. Section 4 describes the data. Section 5 reports the empirical results. Section 6 presents robustness tests focusing on sentiment-climate risk interactions. Section 7 concludes and discusses policy implications.

2. Literature Review

2.1. Climate Risk and Financial Stability: Conceptual Foundations

The literature on climate risk and financial stability has expanded rapidly, with a central distinction between transition risk and physical risk [5] [6]. Transition risk arises from the adjustment toward a low-carbon economy and reflects policy, technological, and market repricing of carbon-intensive assets [7]. Physical risk refers to the direct economic consequences of climate change, including extreme weather events, chronic temperature shifts, droughts, and sea-level rise. While conceptually distinct, both risks interact to shape financial stability outcomes [1] [8].

Network-based frameworks emphasize that climate risk is systemically transmitted through financial linkages rather than absorbed idiosyncratically. Battiston *et al.* [5] show that climate shocks propagate through interbank and portfolio networks. In the Euro Area, while Curcio et al. (2023) document that climate risk in-creases systemic risk in U.S. financial institutions [9]. Literature highlights supervisory constraints in integrating climate risk into prudential frameworks, and [10].

At the bank level, physical risk affects balance sheets through borrower distress, collateral devaluation, and income disruptions, increasing default probabilities and loan losses [11]. Transition risk operates through asset repricing and stranded asset formation in carbon-intensive sectors [12] [13]. Portfolio reallocation toward green assets may further introduce exposure to emerging-sector uncertainty and risk-taking behavior [14].

2.2. Climate Risk and Bank Stock Volatility

Compared with credit risk channels, the equity volatility implications of climate risk remain less explored. Existing studies predominantly rely on accounting or balance-sheet measures rather than market-based variance. Dai and Zhang [14] find that climate policy uncertainty increases bank risk-taking in China. Evidence shows that banks respond to climate shocks by increasing liquidity buffers and secured lending, while Liu *et al.* [15] argue that climate policy uncertainty accelerates creative destruction in carbon-intensive sectors, increasing systemic banking risk. However, these studies do not directly examine stock return vola-

tility.

A parallel literature examines equity market responses to climate uncertainty. [16] documents that climate policy uncertainty increases stock volatility in China. [17] shows similar effects in both China and the U.S., although persistence differs across markets. Literature finds that global spillovers from climate policy uncertainty are short-lived, suggesting that changes in uncertainty drive volatility more than levels. Tedeschi *et al.* [18] extend these findings to European markets, confirming that climate policy shocks significantly affect equity indices.

While these studies establish climate uncertainty as a pricing factor, they typically treat climate risk as a single construct [19] [20] and do not distinguish between transition and physical risk, nor their potentially opposing effects on bank-specific volatility.

2.3. Macro-Financial Uncertainty, Sentiment, and Bank Volatility

Bank stock volatility is also shaped by macro-financial uncertainty and sentiment dynamics. The VIX index captures global risk aversion and has been shown to be a strong predictor of bank equity volatility [21] [22]. Higher VIX is associated with tighter funding conditions, wider credit spreads, and elevated risk premia, increasing bank volatility. Economic policy uncertainty (EPU) similarly affects banking risk. [23] [24] show that EPU captures macroeconomic uncertainty shocks, while [25] finds that it increases loan loss provisioning. Literature shows that EPU raises loan pricing, reflecting risk compensation. Climate policy uncertainty (CPU) extends this framework to environmental regulation [19].

Investor sentiment and consumer confidence act as key transmission modifiers. Behavioral finance suggests that sentiment amplifies or dampens the impact of fundamental shocks on asset prices [26]. When sentiment is fragile, uncertainty shocks generate disproportionate volatility responses. When sentiment is anchored, volatility transmission is attenuated through expectations stability and improved risk absorption capacity.

2.4. Asymmetry between Transition and Physical Risk

A key unresolved issue in the literature is whether transition and physical risks exert asymmetric effects on bank stock volatility. This distinction is theoretically important because the two risk types differ in uncertainty structure and adaptability [5]. Transition risk is endogenous and policy driven. Carbon pricing, regulatory timelines, and subsidy schemes are politically determined and inherently uncertain [27]. This generates Knightian uncertainty, where probability distributions are not well defined [28] [29]. Under such conditions, expectations are highly sensitive to sentiment, amplifying volatility when uncertainty increases.

Physical risk, by contrast, is exogenous and more observable. Although climate change increases the frequency of extreme events, physical risk is increasingly measurable through climate science and pricing models. Financial institutions respond via insurance, provisioning, collateral adjustments, and disaster-response frame-

works [30] [31]. Xu *et al.* [17] further show that banks mitigate physical risk exposure through insurance expansion and digital transformation. As a result, physical risk is more likely to be internalized into prices ex ante, reducing its marginal volatility impact.

Although this asymmetry is often discussed, it has not been directly tested in a unified bank volatility framework. Stroebel and Wurgler [32] note that physical risks are more quantifiable than transition risks, while [33] emphasize forward-looking pricing of transition risk. However, neither examines volatility transmission at the bank equity level.

2.5. Research Gaps and Motivation

This paper addresses three main gaps. First, existing studies largely treat climate risk as a homogeneous construct or focus on climate policy uncertainty alone [19] [20], neglecting the asymmetry between transition and physical risk in driving bank stock volatility. Second, the interaction between macro-financial uncertainty, sentiment (investor sentiment and consumer confidence), and distinct climate risk dimensions remains underexplored, particularly for global systemically important banks (G-SIBs). This is critical because G-SIBs are central transmission nodes in global financial networks. Third, the literature relies predominantly on accounting-based measures (e.g., NPLs, Z-scores, loan spreads), which are backward-looking. In contrast, stock return volatility captures forward-looking market expectations and risk pricing dynamics. A market-based framework is therefore essential for understanding real-time financial stability implications.

By focusing on bank stock volatility and explicitly distinguishing between transition and physical risk—while incorporating sentiment and macro-financial interactions—this paper provides a unified and state-dependent framework for understanding how climate risk is priced in global banking markets.

3. Hypotheses and Research Methodology

This study examines how climate-related risks, macro-financial uncertainty, market liquidity, interest rate changes, global economic policy uncertainty, and sentiment dynamics affect stock return volatility of global systemically important banks (G-SIBs). The hypotheses are grounded in climate-finance theory, banking risk transmission mechanisms, and uncertainty-based asset pricing models [29] [34] [35].

The empirical framework builds on standard asset pricing logic, which posits that bank stock volatility is driven by macro-financial uncertainty, liquidity conditions, policy uncertainty, and climate-related risk factors that jointly affect expected cash flows and discount rates [34] [36] [37].

3.1. Hypotheses

Hypothesis 1: Financial Market Volatility

(H1a) Financial market volatility (VIX) has a positive effect on bank stock vol-

atility.

An increase in VIX reflects heightened global risk aversion and uncertainty about future equity market conditions, leading to portfolio rebalancing and increased bank equity volatility.

(H1b) The equity market volatility calibrated to monetary policy shocks, $EMV_{MP,t}$, positively affects bank stock volatility.

Monetary policy disturbances amplify uncertainty about future interest rates, credit conditions, and profitability, thereby increasing volatility in bank equity markets.

Hypothesis 2: Monetary Policy Effects

(H2) Increases in short-term interest rates, Δr_t, positively affect bank stock volatility.

Higher interest rates improve net interest margins through faster loan repricing relative to deposits, but it may also reduce credit demand and increase default risk, generating ambiguity in future earnings and volatility dynamics [38].

Hypothesis 3: Liquidity Effects

(H3) Increases in market liquidity (ΔLIQ_t) raise bank stock volatility.

Higher turnover enhances price discovery and accelerates the incorporation of macroeconomic and climate-related information into asset prices, increasing measured volatility.

Hypothesis 4: Global Economic Policy Uncertainty

(H4) Increases in global economic policy uncertainty ($\Delta GEPU_t$) raise bank stock volatility.

Elevated global policy uncertainty weakens global activity and increases risk aversion, thereby increasing volatility in bank equity markets.

Hypothesis 5: Climate Risk Uncertainty

(H5a) Changes in climate policy uncertainty (ΔCPU_t) positively affect bank stock volatility.

Climate policy uncertainty increases ambiguity about future regulation, investment costs, and credit quality, thereby raising volatility.

(H5b) Transition risk variance (VTR_t) positively affects bank stock volatility.

Transition risk reflects policy, technological, and market uncertainty associated with the low-carbon transition, increasing uncertainty over the value of carbon-intensive loan portfolios and raising equity volatility.

(H5c) Physical risk variance (VPR_t) negatively affects bank stock volatility.

Although physical risks impair collateral values and borrower performance, their increasing predictability and risk-transfer mechanisms (insurance, provisioning, collateral adjustments) reduce residual uncertainty, thereby lowering volatility.

Hypothesis 6: Consumer Sentiment and Climate Risk

(H6a) Consumer sentiment interacting with VTR_t positively affects bank stock volatility.

During periods of higher sentiment, transition-related uncertainty becomes

more salient, as investors reassess long-term policy and structural risks in a growth-optimistic environment.

(H6b) Consumer sentiment interacting with VPR_t negatively affects bank stock volatility.

Stronger consumer confidence reflects expectations of economic resilience and adaptive capacity, which dampens the volatility impact of physical climate shocks through perceived risk absorption.

Hypothesis 7: Market Sentiment-Volatility Co-movement and Climate Risk

(H7a) The interaction between $EMV_{IVS,t}$ and transition risk variance increases bank stock volatility.

When transition uncertainty is high, sentiment becomes more sensitive to market fear, amplifying expectation revisions and increasing volatility.

(H7b) The interaction between $EMV_{CNS,t}$ and physical risk variance reduces bank stock volatility.

Higher consumer confidence strengthens expectations of economic resilience and recovery capacity, mitigating the volatility impact of physical climate shocks. Note that in the U.S. market, physical climate volatility can generate household income losses and increase the risk of stranded assets, thereby creating additional risks to bank stability.

3.2. Research Methodology

The hypotheses are embedded within an asset pricing framework in which bank stock volatility is driven by macro-financial uncertainty, policy uncertainty, liquidity conditions, and climate-related risk factors [25] [29] [35] [39]. These factors jointly influence expected cash flows and discount rates, thereby determining conditional volatility. The mean equation is specified as:

$$V_{i,t} = C + \beta_1 VIX_t + \beta_2 \Delta r_t + \beta_3 EMV_{MP,t} + \beta_4 \Delta LIQ_t + \beta_5 \Delta GEPU_t + \beta_6 \Delta CPU_t + \varepsilon_{i,t} \quad (1)$$

where $V_{i,t}$ denotes bank stock volatility. C is a constant term, and β_s are estimated parameters. VIX_t measures expected market volatility based on the CBOE volatility index. Δr_t is the change in the 3-month U.S. Treasury bill rate. $EMV_{MP,t}$ captures the covariance between equity market volatility and monetary policy shocks derived from textual analysis of major U.S. newspapers [40]. ΔLIQ_t measures market liquidity, defined as turnover scaled by absolute returns. $GEPU_t$ is the global economic policy uncertainty index [22], and ΔCPU_t is the change in climate policy uncertainty [19].

Given the persistence and clustering in bank stock volatility, the conditional variance is modeled using a GARCH (1, 1) specification:

$$\sigma_{i,t}^2 = \omega + \alpha \varepsilon_{i,t-1}^2 + \beta \sigma_{i,t-1}^2 \quad (2)$$

To accommodate non-normality and fat-tailed return distributions, the error term is assumed to follow a generalized error distribution (GED):

$$\varepsilon_{i,t} \mid \Phi_{t-1} \sim GED\left(0, \sigma_{i,t}^2, \nu\right) \quad (3)$$

The GED specification allows flexible modeling of leptokurtic and platykurtic distributions, which is particularly relevant for bank equity returns that exhibit pronounced tail behavior and volatility clustering [24] [41] [42].

4. Data Description and Summary Statistics

This section describes the data sources, variable construction, and summary statistics used in the empirical analysis. The sample consists of ten global systemically important banks (G-SIBs) from North America, Europe, and to Asia. The dataset includes bank stock volatility, climate-related risk measures, macro-financial uncertainty indicators, and market liquidity variables.

4.1. Data Description

The sample includes the following G-SIBs: Bank of America (BOA), Citigroup (CITI), JPMorgan Chase (JPM), BNP Paribas (BNP), Deutsche Bank (DEUB), HSBC, Mitsubishi UFJ Financial Group (MUFG), Bank of China (BOC), Agricultural Bank of China (ABC), and Industrial and Commercial Bank of China (ICBC). Stock price data from April 2000 to April 2026 are obtained from LSEG DataStream for all banks headquartered in the relevant districts. Some of the Asian banks have later sample starting dates because the required market and explanatory-variable data are not available for the entire April 2000-April 2026 period. We report on the appropriate bank-specific sample starting periods and numbers of observations in **Table 2**.

Bank stock volatility is constructed following [43] as the monthly sum of daily squared returns over a 22-trading-day window, with appropriate adjustments for serial dependence. This measure captures realized volatility at the monthly frequency. Market liquidity is defined as trading volume turnover divided by the absolute value of stock return volatility, consistent with [36] [44][1].

The set of macro-financial variables includes: Financial uncertainty includes stock market volatility of VIX_t, changes in short-term interest rates Δr_t, the equity market volatility calibrated to monetary policy shocks $EMV_{MP,t}$, and global economic policy uncertainty $GEPU_t$, together with the climate policy uncertainty, CPU_t, consumer sentiment, $CONS_t$, transition risk, TR_t and physical risk PR_t were obtained the St Louis FED and Policy Uncertainty Index [22].

Climate risk is captured through transition risk (TR_t) and physical risk (PR_t), constructed by [45] using news-based climate coverage indices that incorporate forward-looking information on climate-related developments. The aggregate climate policy uncertainty index is obtained from [19]. Following [43], the volatility measures of transition and physical risk are constructed as VTR_t: monthly aggregation of daily squared transition risk index values in percentage, and VPR_t: monthly aggregation of daily squared physical risk index values in percentage. Both measures account for persistence and correlation in daily observations. The combined dataset enables analysis of how macro-financial un-

[1]Illiquidity defined by [44] is an inverse of the liquidity we defined.

certainty, liquidity conditions, and distinct dimensions of climate risk jointly affect bank stock volatility across both advanced and emerging market banking systems.

4.2. Summary Statistics

4.2.1. Bank Stock Returns

Table 1 reports descriptive statistics for monthly stock returns across the sample banks. Mean returns vary from −0.38% (CITI) to 0.58% (JPMorgan Chase). Median returns range from 0.13% (BOC) to 1.50% (JPMorgan Chase). Return volatility differs substantially across institutions. Standard deviations range from 5.03% (Agricultural Bank of China) to 10.98% (Deutsche Bank), reflecting heterogeneity in business models, market exposure, and financial structure. Normality is strongly rejected for all return series based on Jarque-Bera statistics, indicating significant skewness and excess kurtosis. These features justify the use of a GED-GARCH framework, which accommodates fat-tailed and non-normal return distributions.

Table 1. Summary of G-SIB stock returns: May 2000-April 2026.

	*R*_BOA	*R*_CITI	*R*_JPM	*R*_BNP	*R*_DEU	*R*_HSBC	*R*_MUFG	*R*_BOC	*R*_ABC	*R*_ICBC
Mean	0.25	−0.38	0.58	0.25	−0.25	0.25	0.28	0.24	0.47	0.36
Median	0.71	0.80	1.35	1.26	0.20	0.39	0.85	0.13	0.32	0.24
Maximum	61.95	55.71	22.98	30.55	43.81	23.07	25.70	40.00	26.37	48.69
Minimum	−64.61	−95.51	−37.18	−66.23	−65.23	−32.25	−54.64	−24.95	−14.02	−21.92
Std. Dev.	10.96	12.26	8.26	10.22	10.98	7.15	9.77	6.74	5.03	7.18
Skewness	−0.77	−1.57	−0.61	−1.55	−0.78	−0.48	−0.92	0.58	0.82	1.31
Kurtosis	11.80	17.01	5.08	10.64	7.36	5.35	6.43	9.81	6.99	12.80
Jarque-Bera	1037.54	2678.60	75.53	883.83	278.66	84.04	189.52	469.88	145.95	998.85
Observations	312	312	312	312	312	312	300	236	188	233

Notes: *R*_Bank is stock return for Bank, where BOA = Bank of America, CITI = CITI bank, JPM = JPMorgan Chase, BNP = BNP Paribas, DEUB = Deutsche Bank, HSBC = The Hong Kong and Shanghai Banking Corporation, MUFG = Mitsubishi Bank, BOC = Bank of China, ABC = Agricultural Bank of China, ICBC = Industrial and Commercial Bank of China. R refers to stock return.

4.2.2. Bank Stock Volatility

Table 2 presents summary statistics for monthly realized volatility. Mean volatility ranges from 34.33% (ABC) to 181.82% (CITI), while median values range from 15.97% (ABC) to 74.25% (Deutsche Bank). Dispersion is substantial across institutions. Standard deviations range from 57.49% (ABC) to 623.26% (CITI), indicating pronounced heterogeneity in volatility dynamics across banks. Jarque-Bera tests strongly reject normality for all volatility series. The distributions exhibit pronounced skewness, leptokurtosis, and fat tails, reinforcing the appropriateness of the GED-GARCH specification to model conditional heteroskedasticity and non-Gaussian behavior.

Table 2. Summary of G-SIB stock volatility: June 2000-April 2026.

	V_t^{BOA}	V_t^{CITI}	V_t^{JPM}	V_t^{BNP}	V_t^{DEUB}	V_t^{HSBC}	V_t^{MUFG}	V_t^{BOC}	V_t^{ABC}	V_t^{ICBC}
Mean	139.31	181.82	90.71	114.33	135.48	55.10	112.34	48.39	34.33	50.34
Median	53.63	53.52	38.75	54.73	74.25	29.22	66.52	17.52	15.97	22.79
Maximum	4503.42	7207.90	2023.18	1095.34	2464.45	746.73	1562.59	655.07	444.54	1018.15
Minimum	1.35	1.25	0.30	3.17	1.86	0.88	3.00	0.02	0.35	0.09
Std. Dev.	403.03	623.26	190.38	169.66	227.85	83.91	148.47	87.42	57.49	95.16
Skewness	7.20	8.21	7.18	3.33	5.99	4.90	4.86	3.84	4.33	6.05
Kurtosis	63.08	78.78	67.71	15.14	50.58	34.82	38.97	20.56	26.50	53.09
Jarque-Bera	49454.41	77910.01	56940.12	2485.159	31201.7	14365.23	17412.23	3640.723	4965.51	26007.38
Sample start	2000.06	2000.06	2000.06	2000.06	2000.06	2000.06	2000.06	2006.07	2010.07	2006.10
Observations	311	311	311	311	311	311	301	238	190	235

Notes: V_t^i is stock volatility for bank *i*. BOA = Bank of America, CITI = CITI bank, JPM = JPMorgan Chase, BNP = BNP Paribas, DEUB = Deutsche Bank, HSBC = The Hong Kong and Shanghai Banking Corporation, MUFG = Mitsubishi Bank, BOC = Bank of China, ABC = Agricultural Bank of China, ICBC = Industrial and Commercial Bank of China. R refers to stock return. The sample period span 2000 through 2026.03, MUFG, BOC, ABC, and ICBC start later.

Table 3 reports pairwise correlations among explanatory variables. VIX_t exhibits moderate positive correlations with $EMV_{MP,t}$, indicating common exposure to equity market risk conditions. By contrast, short-term interest rate changes (Δr_t) display relatively low correlations with other variables, suggesting distinct information content. A notably high correlation (approximately 0.90) is observed between $EMV_{ITR,t}$ and $EMV_{MP,t}$, reflecting overlap in how monetary policy shock and interest rate-policy innovation interact with equity market volatility. $EMV_{MP,t}$, $EMV_{INV,t}$ and $EMV_{CNS,t}$ exhibit moderate positive correlations. ΔLIQ_t and $\Delta GEPU_t$ do not form significant higher correlation with other variables. Overall, the correlation structure does not indicate severe multicollinearity. Variance correlation concerns are limited and are not expected to materially affect coefficient stability in the empirical analysis.

Table 3. Correlation matrix of independent variables for measuring macro and uncertainty.

Corr/t-Statistic	VIX_t	Δr_t	$EMV_{MP,t}$	$EMV_{IRT,t}$	$EMV_{CNS,t}$	$EMV_{IVS,t}$	VTR_t	VPR_t	$\Delta GEPU_t$	ΔLIQ_t
VIX_t	1									

Δr_t	−0.13	1								
	−1.47	-----								
$EMV_{MP,t}$	0.29	0.02	1							
	3.57	0.28	-----							
$EMV_{IRT,t}$	0.17	0.29	0.90	1						
	2.06	3.55	24.24	-----						

Continued

$EMV_{CNS,t}$	0.33	0.10	0.70	0.60	1					
	4.03	1.18	11.41	8.83	-----					
$EMV_{IVS,t}$	0.05	0.01	0.48	0.42	0.61	1				
	0.63	0.09	6.46	5.44	9.08	-----				
VTR_t	−0.18	−0.08	−0.15	−0.15	−0.12	−0.05	1			
	−2.15	−0.99	−1.74	−1.73	−1.38	−0.56	-----			
VPR_t	−0.12	−0.07	−0.05	−0.10	0.00	0.02	−0.03	1		
	−1.41	−0.78	−0.61	−1.18	0.01	0.20	−0.34	-----		
$\Delta GEPU_t$	0.04	−0.01	0.23	0.12	0.14	0.12	0.00	−0.06	1	
	0.45	−0.06	2.76	1.39	1.67	1.40	−0.04	−0.65	-----	
ΔLIQ_t	−0.08	−0.09	−0.07	−0.09	−0.04	−0.05	−0.02	0.05	0.08	1
	−0.96	−1.00	−0.83	−1.06	−0.49	−0.54	−0.24	0.60	0.96	-----

Notes: VIX_t is the CBOE volatility index to measure the market's expectation of 30-day volatility for the S&P 500. Δr denotes changes in short-term interest rates. $EMV_{MP,t}$, $EMV_{IRT,t}$, $EMV_{CNS,t}$, and $EMV_{IVS,t}$ denote equity market volatility calibrated to monetary policy, interest rate policy, consumer sentiment and investor sentiment, respectively, VTR_t and VPR_t are variances of transition and physical risks, $\Delta GEPU_t$ is changes in global economic policy uncertainty, ΔLIQ refers to changes in bank liquidity proxied by Bank of America.

5. Empirical Evidence

Equations (1)-(3) are estimated and the main results are reported in Table 4, which presents baseline estimates for using VIX_t, $EMV_{MP,t}$, Δr_t, ΔLIQ_t, and $\Delta GEPU_t$. Table 5 extends the specification by incorporating climate policy uncertainty (ΔCPU_t). Because the Table 4 results are nested within Table 5 and yield qualitatively similar conclusions, the discussion focuses on Table 5 unless otherwise noted.

Table 4. Impact of financial uncertainty on G-SIB stock variances using GED-GARCH estimates.

	C	VIX_t	$EMV_{MP,t}$	Δr_t	ΔLIQ_t	$\Delta GEPU_t$	ω	ε_{t-1}^2	σ_{t-1}^2	$\overline{R}^2$
V_t^{BOA}	−49.523	3.566	10.500	−5.729	13.750	0.105	37.206	0.583	0.503	0.32
	−13.37	12.58	31.98	−10.65	4.19	14.19	0.78	0.59	0.94	
V_t^{CITI}	−68.893	4.906	10.509	−4.316	32.754	0.368	92.820	21.619	0.210	0.35
	−19.18	20.46	35.30	−15.62	17.46	14.18	0.55	0.48	0.24	
V_t^{JPM}	−9.020	2.090	3.678	−2.199	8.137	0.201	12.914	0.580	0.506	0.16
	−3.54	13.28	22.08	−16.18	18.49	14.20	1.02	0.95	1.56	
V_t^{BNP}	−49.859	5.043	5.728	−7.266	41.041	0.598	98.022	1.027	0.032	0.15
	−8.31	14.88	7.87	−8.42	7.77	8.85	2.07	1.16	0.16	
V_t^{DEUB}	−47.696	4.208	8.308	−6.588	50.194	0.172	80.123	0.957	0.477	0.15
	−11.63	18.59	18.55	−6.98	24.80	2.33	1.00	0.83	1.18	

Continued

V_t^{HSBC}	−26.252	1.848	5.197	−0.019	3.314	0.085	11.785	0.521	0.857	0.26
	−20.32	13.18	16.50	−0.07	3.34	4.44	0.36	0.36	2.52	
V_t^{MUFG}	47.966	−1.680	9.812	−0.993	107.859	0.301	64.364	−0.013	0.659	0.19
	9.50	−8.66	12.73	−5.14	17.93	3.93	0.22	−0.17	0.41	
V_t^{BOC}	20.136	−0.996	1.499	−1.214	17.792	0.163	10.736	1.588	0.112	0.11
	21.97	−12.35	16.83	−8.28	16.89	10.56	2.09	1.41	0.48	
V_t^{ABC}	18.697	−0.846	1.652	−0.455	3.619	0.065	12.537	3.013	0.041	0.11
	14.00	−11.44	9.95	−12.11	12.97	3.86	2.12	1.41	0.37	
V_t^{ICBC}	22.338	−0.800	1.505	−1.468	18.800	−0.100	22.680	2.260	0.036	0.10
	18.82	−11.15	13.38	−5.79	14.63	3.73	1.94	1.43	0.21	

Notes: Dependent variable is banks stock variance, V_t^i, where superscript i refers to BOA = Bank of America, CITI = CITI bank, JPM = JPMorgan Chase, BNP = BNP Paribas, DEUB = Deutsche Bank, HSBC = The Hong Kong and Shanghai Banking Corporation, MUFG = Mitsubishi Bank, BOC = Bank of China, CCB = China Construction Bank, ICBC = Industrial and Commercial Bank of China. VIX_t is the CBOE volatility index to measure the market's expectation of 30-day volatility for the S&P 500. Δr_t is changes in short-term interest rates. $EMV_{MP,t}$ is equity market volatility calibrated to monetary policy; LIQ_t refers to bank liquidity, which is trading volume turnover divided by the absolute value of stock return; Δr_t denotes changes in short-term interest rates. $GEPU_t$ refers to global economic policy uncertainty. Δ is a differenced operator. coefficients of ω were multiplied by 10^{-2}. The numbers in the first row are the estimated coefficients; the second row contains the z-statistics. The critical values of z-distribution at the 1%, 5%, and 10% levels of significance are 2.63, 1.98, and 1.66, respectively.

Table 5. Effects of financial volatility and climate policy uncertainty on G-SIB stock variances: GED-GARCH Estimates model.

	C	VIX_t	$EMV_{MP,t}$	Δr_t	ΔLIQ_t	$\Delta GEPU_t$	ΔCPU_t	ω	ε_{t-1}^2	σ_{t-1}^2	$\bar{R}^2$
V_t^{BOA}	−50.963	3.483	9.532	−3.367	28.774	0.339	11.606	30.185	0.390	0.531	0.31
	−11.02	14.83	16.12	−6.53	6.73	6.59	4.52	0.80	0.65	1.05	
V_t^{CITI}	−58.029	4.547	7.415	−3.191	29.637	0.202	0.015	26.156	0.835	0.102	0.30
	−15.05	19.95	25.08	−16.79	6.20	5.25	3.47	2.08	1.40	0.57	
V_t^{JPM}	−10.136	2.091	3.624	−1.921	4.188	0.204	2.148	32.774	1.103	0.048	0.16
	−2.97	13.25	9.21	−6.47	1.26	5.89	2.01	1.72	0.95	0.16	
V_t^{BNP}	−14.070	4.242	1.953	−4.048	49.609	0.588	3.070	62.813	1.352	0.002	0.08
	−2.63	19.10	2.50	−4.73	8.08	8.00	3.07	2.91	1.95	0.05	
V_t^{DEUB}	−44.658	3.378	9.817	−3.804	13.043	0.482	12.277	50.368	0.531	0.398	0.14
	−8.39	13.61	22.00	−5.97	5.72	6.84	6.63	1.34	154.00	1.14	
V_t^{HSBC}	−26.250	1.876	5.363	−0.167	−9.035	0.002	4.537	10.008	0.602	0.790	0.27
	−14.36	10.25	12.42	−0.42	−3.28	2.10	2.83	0.36	0.44	1.75	

Continued

V_t^{MUFG}	47.437	−1.636	9.784	−0.985	105.597	0.247	14.510	12.951	−0.019	0.943	0.18
	11.77	−9.32	16.33	−2.09	21.31	3.63	4.33	0.67	−0.69	9.34	
V_t^{BOC}	26.038	−0.794	3.608	−4.532	37.719	−0.108	2.894	87.031	1.289	0.078	0.04
	18.66	−12.08	11.53	−28.59	49.22	−10.30	11.36	1.12	0.83	0.14	
V_t^{ABC}	−29.327	5.160	7.770	−17.054	2.303	0.307	0.098	278.350	1.398	0.743	0.22
	−9.756	30.526	11.569	−30.720	46.934	5.369	3.180	0.487	0.504	1.767	
V_t^{ICBC}	23.270	−0.792	1.578	−1.965	21.368	−0.180	8.446	10.986	2.031	0.067	0.09
	18.79	−10.64	15.02	−12.71	17.87	−7.74	16.41	1.97	1.46	0.34	

Notes: Dependent variable is banks stock variance, V_t^i, where superscript i refers to BOA = Bank of America, CITI = CITI bank, JPM = JPMorgan Chase, BNP = BNP Paribas, DEUB = Deutsche Bank, HSBC = The Hong Kong and Shanghai Banking Corporation, MUFG = Mitsubishi Bank, BOC = Bank of China, CCB = China Construction Bank, ICBC = Industrial and Commercial Bank of China. VIX_t is the CBOE volatility index to measure the market's expectation of 30-day volatility for the S&P 500. Δr_t is changes in short-term interest rates. $EMV_{MP,t}$ is equity market volatility calibrated to monetary policy. $\Delta GEPU_t$ is change in global economic policy uncertainty. LIQ_t refers to bank liquidity, which is trading volume turnover divided by the absolute value of stock return; Δr_t denotes changes in short-term interest rates. ΔCPU_t denotes the climate policy uncertainty. Notation represents the change in a variable. Coefficients of ω were multiplied by 10^{-2}. The numbers in the first row are the estimated coefficients; the second row contains the z-statistics. The critical values of z-distribution at the 1%, 5%, and 10% levels of significance are 2.63, 1.98, and 1.66, respectively.

5.1. Equity Market Volatility

The coefficients on VIX_t are positive and statistically significant at the 1% level for most U.S. and European banks, supporting **H1a**. This result confirms that global market uncertainty is a key driver of bank stock volatility, consistent with standard systematic risk and volatility spillover channels [46]. For Bank of America, Citigroup, JPMorgan, BNP Paribas, Deutsche Bank, and HSBC, increases in VIX are associated with higher bank stock volatility. These institutions are highly integrated into global capital markets through trading, investment banking, and wholesale funding activities. As global risk aversion rises, funding conditions tighten, counterparty risk increases, and valuation uncertainty in trading portfolios intensifies, transmitting directly into higher equity volatility via contagion effect [47].

In contrast, the coefficients for MUFG, Bank of China, ABC and ICBC are negative. This divergence reflects structural differences in financial market openness and institutional design. In these economies, capital controls, state ownership, and policy-driven stabilization mechanisms weaken the transmission of global volatility shocks. In particular, capital account restrictions limit cross-border portfolio rebalancing during stress periods, while state intervention and implicit guarantees help stabilize equity markets when global uncertainty rises. As a result, increases

in VIX may coincide with reduced domestic volatility due to stabilizing capital flows and insulation policy responses [48].

5.2. Interest Rate Effects

The coefficients on short-term interest rate changes (Δr_t) are predominantly negative and statistically significant, supporting **H2**. This result suggests that monetary tightening, on average, reduces bank stock volatility. This effect is consistent with the net interest margin (NIM) stabilization channel. When interest rates rise, lending rates typically adjust faster than deposit rates due to deposit stickiness, leading to margin expansion and more stable earnings expectations [49]. Improved profitability reduces uncertainty about future cash flows and thereby lowers equity volatility.

In addition, as noted by [50], gradual and well-communicated tightening cycles reduce policy uncertainty by allowing markets to adjust predictably to rate changes. This reduces informational shocks associated with monetary policy and dampens volatility in bank equity markets.

5.3. Monetary Policy-Induced Market Volatility

The covariance term $EMV_{MP,t}$ is positive and statistically significant across all banks, strongly supporting **H1b**. This result indicates that when equity market volatility and monetary policy shocks co-move, bank stock volatility increases uniformly, regardless of institutional setting. The coefficient captures episodes in which monetary authorities respond to global financial stress, generating a regime of policy intervention and uncertainty about future policy paths.

Two mechanisms are relevant. First, monetary easing during periods of elevated market volatility compresses net interest margins, increasing uncertainty about bank profitability [51] [52]. Second, policy interventions themselves introduce forward-looking uncertainty regarding duration and broader regulatory stance, amplifying volatility in equity markets. Compared with VIX alone, the covariance measure better captures systemic macro-financial stress. While VIX reflects U.S.-centric risk sentiment, $EMV_{MP,t}$ identifies monetary policy responses to financial stress or event, making it more relevant for internationally active banks.

5.4. Liquidity Effects

The estimated coefficients on ΔLIQ_t are predominantly positive and statistically significant, supporting **H3**. Higher liquidity is associated with increased bank stock volatility for most banks (9 out of 10 cases). This result is consistent with two complementary channels. First, from a market microstructure perspective, higher turnover enhances price discovery and accelerates the incorporation of macroeconomic and climate-related information into prices, increasing realized volatility [53]. Second, higher liquidity may amplify volatility through noise-trading channels. Increased trading activity attracts short-horizon and momentum-driven investors, generating feedback effects that push prices away from funda-

mentals and increase volatility [54]. HSBC represents an exception, where the liquidity-volatility relationship is negative. This may reflect its role as a global market-maker and the stabilizing influence of institutional investor flows, which can counteract noise-trader effects.

5.5. Global Economic Policy Uncertainty

The coefficients on $\Delta GEPU_t$ are positive and statistically significant across most of banks, confirming **H4**. Higher global economic policy uncertainty increases bank stock volatility by weakening macroeconomic expectations and increasing risk premium [46]. Uncertainty about trade policy, regulation, taxation, and fiscal frameworks reduces investment and output growth, thereby increasing borrower default risk and weakening bank balance sheets. Consistent with [55], policy uncertainty raises both expected returns and volatility by increasing disagreement about future cash flows. For banks, this effect is amplified due to their leverage and exposure to macro-sensitive loan portfolios. The two exceptions are Bank of China and ICBC, where policy intervention may help preserve market stability.

5.6. Climate Policy Uncertainty

Table 5 shows that changes in climate policy uncertainty (ΔCPU_t) have a positive and statistically significant effect on bank stock volatility across all institutions, supporting **H5a**. This result indicates that climate policy uncertainty is an important additional source of financial instability for global banks. CPU reflects ambiguity regarding the timing, scale, and implementation of climate-related regulations, including carbon pricing, fossil fuel phase-outs, and green transition subsidies [29].

Such uncertainty affects banks through multiple channels. First, it complicates credit risk assessment for carbon-intensive borrowers, increasing uncertainty about future default probabilities. Second, it raises the risk of stranded assets in sectors such as fossil fuels and heavy industry, particularly in long-term project finance and syndicated lending exposures [5] [28]. From a market perspective, increased CPU weakens firm investment and cash-flow stability, thereby increasing loan default risk and bank equity volatility. These findings are consistent with [16] [17] who document significant volatility effects of climate policy uncertainty in equity markets.

Overall, the results strongly support the hypothesized framework. Financial market volatility, monetary policy-market interactions, global policy uncertainty, and climate policy uncertainty all exert significant effects on bank stock volatility. [2] Importantly, the results also reveal structural heterogeneity: while advanced market banks exhibit stronger volatility transmission from global financial shocks, Asian banks display partial insulation due to institutional features such as capital

[2]The volatility (measured by standard deviation and variance) from currency markets is significant in explaining the excess returns or variance [56], suggesting that the excess returns are indeed reward for risk-taking. However, the exchange rate volatility and its effect on stock variance is excluded from this study.

controls and state ownership. These differences highlight the importance of distinguishing between global market integration and domestic stabilization mechanisms in explaining bank volatility dynamics.

6. Evidence of Climate Risk Variances and Market Sentiments

6.1. Baseline Asymmetry between Transition and Physical Risk

Table 6 presents the baseline effects of climate risk variances on bank stock volatility, distinguishing between transition risk variance (VTR) and physical risk variance (VPR). The results reveal a clear and statistically significant asymmetry. First, the coefficient on VTR is positive and statistically significant, supporting **H5b** that transition risk variance increases bank stock volatility. This result is consistent with the view that transition risk reflects policy-driven and market-driven uncertainty associated with the low-carbon transition. Such uncertainty affects expectations about future profitability of carbon-intensive lending portfolios, particularly through repricing of stranded assets and shifting regulatory regimes. Because the timing and scale of climate policies remain inherently uncertain, higher transition risk variance amplifies uncertainty about banks' future cash flows and increases equity volatility. Second, the coefficient on VPR is negative and statistically significant, suggesting that higher physical risk variance reduces bank stock volatility that confirms **H5c.** This finding reflects the distinct transmission channel of physical climate risk. Although physical events can impair borrower solvency and collateral values, banks are partially insulated through insurance coverage, collateral requirements, and risk-sharing arrangements. Moreover, physical risk is increasingly anticipated and incorporated into pricing models, reducing its marginal "surprise" component when variance increases. As a result, higher physical risk variance is associated with a more stabilizing effect on bank equity volatility.

Overall, the evidence in Table 6 confirms a fundamental asymmetry: transition risk operates through uncertainty amplification channels, while physical risk operates through adaptation and partial risk transfer mechanisms that dampen volatility.

Table 6. Effects of financial volatility and climate risk variances on G-SIB stock variances using the GED-GARCH model.

	C	VIX_t	$EMV_{MP,t}$	Δr_t	ΔLIQ_t	$\Delta GEPU_t$	VTR_t	VPR_t	ω	ε_{t-1}^2	σ_{t-1}^2	$\overline{R}^2$
V_t^{BOA}	−17.011	1.891	7.958	−0.598	12.394	0.435	0.171	−0.617	30.271	0.785	0.595	0.21
	−3.96	7.02	28.32	−6.07	3.51	12.89	2.75	−4.73	0.57	0.61	1.06	
V_t^{CITI}	−86.371	4.146	12.491	−1.623	17.547	0.233	0.254	−0.023	53.731	0.651	0.425	0.34
	−14.52	15.05	17.35	−3.02	3.81	6.53	2.62	−3.55	0.78	0.70	0.76	
V_t^{JPM}	−29.517	2.264	5.528	−1.092	−1.012	0.203	0.077	−0.034	10.707	0.358	0.550	0.22
	−16.04	18.64	44.39	−6.89	−3.90	12.09	2.49	−1.76	0.92	0.77	1.44	

Continued

V_t^{BNP}	−16.084	2.997	6.353	−3.575	44.136	0.503	0.115	−0.002	54.367	0.527	0.017	0.21
	−4.22	10.23	7.86	−4.74	6.70	7.92	2.57	−4.52	2.91	1.17	0.16	
V_t^{DEUB}	−28.000	3.022	10.477	−7.751	36.217	0.104	0.404	−0.001	57.468	0.622	0.572	0.19
	−4.94	10.09	12.17	−14.42	14.17	2.94	4.12	−6.04	0.71	0.72	1.18	
V_t^{HSBC}	−22.869	1.761	4.599	−0.877	4.873	−0.078	0.176	−0.380	15.270	0.304	0.839	0.17
	−8.64	8.13	11.63	−8.06	2.11	−12.41	12.17	−6.25	0.61	0.84	5.43	
V_t^{MUFG}	45.718	−1.571	9.806	−1.666	114.622	0.376	0.216	−1.631	10.280	0.018	0.682	0.20
	13.45	−5.98	17.22	−3.36	28.01	9.35	1.72	−15.91	0.10	0.05	0.22	
V_t^{BOC}	−39.221	−0.992	1.406	−2.220	26.728	−0.072	0.194	−0.080	13.893	1.401	0.031	0.07
	19.65	−8.64	5.54	−11.95	20.88	−4.59	4.01	−6.16	2.49	1.44	0.26	
V_t^{ABC}	22.120	−0.816	1.508	−0.812	18.246	−0.327	0.102	−0.135	63.051	2.140	0.026	0.12
	15.449	−8.932	5.860	−3.090	9.225	−10.446	2.859	−2.520	1.860	1.871	0.254	
V_t^{ICBC}	29.985	−1.193	2.094	−3.300	9.687	−0.108	0.322	−0.506	19.412	1.942	0.081	0.06
	13.35	−10.80	17.91	−12.67	16.16	−27.28	26.78	−3.48	1.50	1.25	0.27	

Notes: Dependent variable is banks stock variance, V_t^i, where superscript i refers to BOA = Bank of America, CITI = CITI bank, JPM = JPMorgan Chase, BNP = BNP Paribas, DEUB = Deutsche Bank, HSBC = The Hong Kong and Shanghai Banking Corporation, MUFG = Mitsubishi Bank, BOC = Bank of China, CCB = China Construction Bank, ICBC = Industrial and Commercial Bank of China. VIX_t is the CBOE volatility index to measure the market's expectation of 30-day volatility for the S&P 500. Δr_t denotes changes in short-term interest rates. $EMV_{MP,t}$ is equity market volatility calibrated to monetary policy; LIQ_t refers to bank liquidity, which is trading volume turnover divided by the absolute value of stock return; Δr_t denotes changes in short-term interest rates. $GEPU_t$ refers to global economic policy uncertainty. CPU_t denotes the climate policy uncertainty. Δ represents the change in a variable. coefficients of ω were multiplied by 10^{-2}. VTR_t and VPR_t are variances of transition and physical risks, coefficients of VTR_t and VPR_t were multiplied by 10^3. Δ is a difference operator. coefficients of ω were multiplied by 10^{-2}. The numbers in the first row are the estimated coefficients; the second row contains the z-statistics. The critical values of z-distribution at the 1%, 5%, and 10% levels significance are 2.63, 1.98, and 1.66, respectively.

6.2. Sentiment-Dependent Transmission of Climate Risk

Table 7 extends the analysis by examining how climate risk variances interact with sentiment indicators, namely consumer confidence, revealing a regime-dependent amplification mechanism.

6.2.1. Transition Risk and Consumer Confidence (H6a)

The interaction between consumer sentiment and transition risk variance ($CONS_t \cdot VTR_t$) is positive and statistically significant. This finding indicates that higher consumer confidence strengthens the volatility-enhancing effect of transition risk. This result can be interpreted through an expectations-revision channel. Periods of strong consumer confidence are typically associated with economic expansion, stronger credit demand, and optimistic growth expectations. In such environ-

ments, investors place greater weight on future growth opportunities and therefore react more sensitively to uncertainty about climate policies, carbon pricing trajectories, and technological transitions. Because transition risk directly affects long-run profitability and business models of both banks and their borrowers, uncertainty about the speed and direction of the green transition leads to larger revisions in expectations when sentiment is optimistic, thereby amplifying bank stock volatility.

Table 7. Effects of financial volatility and consumer sentiment interacting with climate risk variances on G-SIB stock variances using the GED-GARCH model.

	C	VIX_t	$EMV_{MP,t}$	Δr_t	ΔLIQ_{tt}	$\Delta GEPU_t$	$CONS_t \cdot VTR_t$	$CONS_t \cdot VPR_t$	ω	ε_{t-1}^2	σ_{t-1}^2	$\bar{R}^2$
V_t^{BOA}	−19.124	1.587	7.708	−1.285	16.917	0.403	0.002	−0.006	20.224	0.305	0.566	0.17
	−3.34	6.42	14.66	−2.13	2.89	5.79	4.32	−6.36	0.76	0.82	1.19	
V_t^{CITI}	−83.282	4.167	12.890	−1.808	8.829	0.483	0.004	−0.005	34.518	0.399	0.531	0.35
	−19.10	21.07	19.22	−4.98	2.71	9.61	2.22	−2.53	0.79	0.78	1.11	
V_t^{JPM}	−27.635	2.231	5.641	−1.354	−6.191	0.197	0.001	−0.002	11.020	0.270	0.575	0.22
	−10.45	15.34	17.76	−7.78	−6.71	7.51	3.00	−2.18	0.84	0.72	1.35	
V_t^{BNP}	−11.150	3.347	7.746	−8.914	90.146	0.718	0.001	−0.027	38.933	0.137	0.508	0.28
	−3.30	9.59	10.67	−6.47	9.63	4.68	2.41	−6.90	0.66	0.70	0.76	
V_t^{DEUB}	−21.123	3.956	13.004	−9.505	44.284	1.319	0.003	−0.013	61.593	0.201	0.826	0.36
	−1.71	6.40	8.88	−7.31	6.04	7.22	16.98	−5.48	0.24	0.26	1.27	
V_t^{HSBC}	−22.224	1.686	4.673	−1.289	−7.655	−0.031	0.002	−0.003	9.590	0.461	0.686	0.18
	−9.73	9.71	12.63	−3.72	−2.27	−3.41	21.55	−14.20	0.47	0.51	1.32	
V_t^{MUFG}	−182.335	1.580	8.226	−2.869	112.012	0.501	0.002	−0.004	38.444	−0.011	0.581	0.28
	−15.84	5.07	7.35	−2.69	19.76	5.04	5.77	−1.97	0.50	−0.65	0.67	
V_t^{BOC}	26.973	−1.150	1.812	−1.515	26.785	−0.151	0.002	−0.001	13.709	0.945	0.049	0.03
	11.98	−11.24	14.24	−5.21	23.99	−5.33	2.65	−2.07	2.56	1.42	0.30	
V_t^{ABC}	21.324	−0.880	1.737	−2.540	27.578	−0.428	0.012	−0.001	109.585	0.818	0.296	0.12
	15.529	−8.886	13.031	−6.625	12.749	−33.402	2.036	−3.029	1.436	1.344	1.322	
V_t^{ICBC}	32.265	−0.857	2.390	−3.974	29.091	−0.407	0.001	−0.001	11.955	1.007	0.494	0.05
	14.46	−16.39	7.09	−14.83	20.34	−13.10	7.92	−4.59	0.91	0.85	1.27	

Notes: The dependent variable is bank stock variance V_t^i, where superscript i denotes Bank of America (BOA), Citigroup (CITI), JPMorgan Chase (JPM), BNP Paribas (BNP), Deutsche Bank (DEUB), HSBC Holdings (HSBC), Mitsubishi UFJ Financial Group (MUFG), Bank of China (BOC), Agricultural Bank of China (ABC), and Industrial and Commercial Bank of China (ICBC). VIX_t is the CBOE Volatility Index. Δr_t denotes changes in the short-term interest rate. $EMV_{MP,t}$ is equity market volatility calibrated to monetary policy; LIQ_t refers to bank liquidity, which is trading volume turnover divided by the absolute value of stock return; ΔCPU_t denotes changes in climate policy uncertainty. Δ denotes first differences of the respective variables. All volatility-related coefficients of ω are scaled by 10^{-2} for presentation purposes. $CONS_t$ denotes consumer sentiment. Coefficients of $CONS_t \cdot VTR_t$ and $CONS_t \cdot VPR_t$ were multiplied by 10^3. VTR and VPR are the variances of transition and physical risks, respectively. Δ represents the change in a variable. The numbers in the first row are the estimated coefficients; the second row contains the z-statistics. The critical values of *z*-distribution at the 1%, 5%, and 10% levels of significance are 2.63, 1.98, and 1.66, respectively.

6.2.2. Physical Risk and Consumer Confidence (H6b)

In contrast, the interaction between consumer sentiment and physical risk variance ($CONS_t \cdot VPR_t$) is negative and statistically significant. This indicates that higher consumer confidence dampens the volatility impact of physical climate risk. This result is consistent with a resilience and adaptation channel. Strong consumer confidence reflects favorable macroeconomic conditions and expectations of sustained income growth. Under such conditions, households, firms, and financial institutions are perceived to be better able to absorb and recover from physical shocks such as floods, droughts, or wildfires. In addition, high confidence may reflect expectations of effective public disaster response systems and improved adaptive infrastructure. Consequently, physical risk uncertainty is less likely to translate into heightened financial market stress when sentiment is strong, reducing its impact on bank stock volatility.

Taking together, the results in Table 7 demonstrate that consumer sentiment plays a dual and asymmetric role in climate risk transmission. It amplifies the impact of transition risk by increasing sensitivity to policy-driven uncertainty, while simultaneously attenuating the impact of physical risk through perceived economic resilience and adaptation capacity. These findings reinforce the central implication of this study: climate risks are not homogeneous in their financial effects, and their transmission to bank stock volatility critically depends on both risk type and prevailing sentiment conditions [57].

6.3. Market Sentiment, Stock Volatility, and Climate Risk Interactions (H1 - H7)

Table 8 extends the analysis to a broader set of macro-financial and sentiment-linked variables, highlighting how climate risk effects are shaped by market conditions and institutional heterogeneity across G-SIBs. The results reinforce the central theme of this paper: climate risk transmission to bank stock volatility is both state-dependent and sentiment-dependent, and it differs systematically across risk types and banking systems.

6.3.1. Volatility (VIX) and Institutional Heterogeneity (H1A)

Evidence in Table 8 clearly indicates that coefficients on VIX display a clear cross-regional divergence. For Bank of America, Citigroup, JPMorgan Chase, BNP Paribas, Deutsche Bank, and HSBC, the VIX coefficient is positive and statistically significant. This result is consistent with standard volatility spillover mechanisms as stated in **H1A**. These institutions are deeply integrated into global capital markets, and increases in global uncertainty directly affect trading revenues, funding conditions, and counterparty risk, thereby amplifying equity volatility.

In contrast, for MUFG, Bank of China, Agricultural Bank of China, and ICBC, the VIX coefficient is negative. This pattern reflects structural insulation from global financial turbulence. Capital controls, state ownership, and policy intervention mechanisms reduce the pass-through of global risk sentiment into domestic equity volatility. In addition, during periods of elevated global uncertainty, im-

plicit guarantees and policy-stabilizing actions may induce countercyclical inflows into domestic banking systems, dampening volatility.

Table 8. Effect of financial volatility and investor & consumer sentiments interacting with climate risk variances on G-SIB stock variances using the GED-GARCH model.

	C	VIX_t	$EMV_{MP,t}$	Δr_t	ΔLIQ_t	$\Delta GEPU_t$	$EMV_{IVS,t} \cdot VTR_t$	$EMV_{CNS,t} \cdot VPR_t$	ω	ε_{t-1}^2	σ_{t-1}^2	$\bar{R}^2$
V_t^{BOA}	−20.992	1.822	7.655	−0.889	48.689	0.373	0.873	−0.033	18.032	0.435	0.583	0.17
	−4.24	6.79	19.37	−6.96	9.10	9.25	3.01	−8.24	0.79	0.83	1.39	
V_t^{CITI}	−87.429	4.294	12.991	−1.784	20.037	0.566	0.328	−0.027	58.945	0.272	0.977	0.35
	−43.46	32.82	33.80	−5.10	5.46	19.38	2.92	−4.78	0.57	0.14	12.12	
V_t^{JPM}	−28.674	2.336	5.314	−1.162	1.892	0.265	0.449	−0.064	15.936	0.357	0.620	0.22
	−41.87	96.91	31.05	−10.46	2.45	24.20	2.74	−4.23	0.65	0.60	1.24	
V_t^{BNP}	−23.256	3.373	8.393	−4.715	69.267	0.333	0.539	−0.171	78.892	0.033	0.714	0.26
	−5.21	23.41	12.09	−7.69	14.06	15.50	2.58	−3.10	0.19	0.14	0.49	
V_t^{DEUB}	−31.699	4.105	13.748	−8.700	44.695	1.214	0.665	−1.083	57.713	1.092	0.628	0.36
	−4.96	8.98	13.28	−7.20	8.11	7.56	3.94	−6.97	0.40	0.58	1.03	
V_t^{HSBC}	−22.637	1.819	4.656	−1.365	2.987	−0.100	0.959	−0.411	16.915	0.264	0.896	0.14
	−8.18	8.73	13.56	−5.65	1.96	−3.86	6.08	−10.67	0.61	0.70	7.75	
V_t^{MUFG}	35.728	−1.536	11.182	−1.510	132.633	0.341	0.213	−0.701	73.392	−0.001	0.618	0.21
	6.55	−6.70	13.34	−3.62	22.01	7.07	4.36	−3.66	0.06	0.00	0.10	
V_t^{BOC}	34.901	−0.918	2.989	−4.677	42.489	−0.212	0.240	−0.130	37.084	0.455	0.714	0.07
	11.93	−8.68	6.39	−13.64	20.95	−6.79	58.18	−2.74	0.56	0.66	1.66	
V_t^{ABC}	23.230	−0.888	2.817	−2.063	23.952	−0.514	0.255	−0.035	22.105	1.581	0.007	0.05
	9.92	−8.90	9.43	−7.39	13.17	−13.66	6.89	−2.48	1.64	1.31	0.03	
V_t^{ICBC}	20.301	−0.683	1.239	−1.266	15.842	−0.057	0.773	−0.108	4.970	1.761	0.029	0.11
	12.35	−6.12	4.62	−6.51	7.88	−6.75	2.21	−2.42	2.51	2.10	0.30	

Notes: The dependent variable is bank stock variance V_t^i, where superscript i denotes Bank of America (BOA), Citigroup (CITI), JPMorgan Chase (JPM), BNP Paribas (BNP), Deutsche Bank (DEUB), HSBC Holdings (HSBC), Mitsubishi UFJ Financial Group (MUFG), Bank of China (BOC), Agricultural Bank of China (ABC), and Industrial and Commercial Bank of China (ICBC). VIX_t is the CBOE Volatility Index. Δr_t denotes changes in the short-term interest rate. $\text{Cov}(\sigma_t, MP_t)$ measures the covariance between equity market volatility and monetary policy shocks. $GEPU_t$ denotes global economic policy uncertainty. LIQ_t measures stock liquidity, defined as trading volume turnover divided by the absolute value of stock returns. ΔCPU_t denotes changes in climate policy uncertainty. Δ denotes first differences of the respective variables. All volatility-related coefficients ω are scaled by 10^{-2} for presentation purposes. The interaction term $EMV_{IVS,t} \cdot VTR_t$ and $EMV_{IVS,t} \cdot VPR_t$ denote the equity market volatility calibrated to investor sentiment times transition risk variance (VTR_t) and physical risk variance (VPR_t). The slopes of interaction coefficients are scaled by 10^{-3} for presentation purposes. Reported values in the first row are estimated coefficients; the second row reports z-statistics. Statistical significance is based on standard normal critical values of 2.63, 1.98, and 1.66 at the 1%, 5%, and 10% levels, respectively.

6.3.2. Monetary Policy-Market Volatility Covariance (H1b)

The covariance between equity market volatility and monetary policy actions, $EMV_{MP,t}$, is positive and statistically significant across all banks. This uniformity supports **H1b** and indicates that monetary policy causes global shocks, constituting a common volatility transmission channel. This result suggests that when monetary authorities respond to periods of heightened market stress, policy interventions—such as liquidity injections or rate adjustments—introduce additional uncertainty regarding future policy normalization, regulatory stance, and interest rate trajectories. As a result, rather than stabilizing bank equity markets unconditionally, policy responses become a second-order source of volatility through expectations re-pricing and margin compression effects.

6.3.3. Short-Term Interest Rates and Liquidity Effects (H2 - H3)

Consistent with **H2**, changes in short-term interest rates (Δr_t) exert a uniformly negative effect on bank stock volatility. This result reflects improved net interest margin stability during tightening cycles, as lending rates adjust faster than deposit rates, reducing earnings uncertainty. More broadly, gradual and predictable policy tightening reduces uncertainty about the future path of interest rates, thereby dampening volatility.

Liquidity changes (ΔLIQ_t) are predominantly positive and statistically significant, supporting **H3**. Higher liquidity enhances trading activity and accelerates information incorporation into prices, but it may also amplify noise trading and feedback effects, leading to higher measured volatility. A small subset of banks with strong institutional investor bases exhibit weaker or negative effects, consistent with the presence of stabilizing arbitrage capital.

6.3.4. Global Economic Policy Uncertainty (H4)

The coefficients on global economic policy uncertainty ($\Delta GEPU_t$) are positive for U.S. and European banks, supporting **(H4)**, while negative for several Asian banks. For globally integrated institutions, higher GEPU increases uncertainty about macroeconomic conditions, regulatory frameworks, and borrower credit quality, thereby raising stock volatility. In contrast, for banks such as ABC, BOC, ICBC, HSBC operating in more policy-coordinated or state-influenced financial systems, elevated global uncertainty may be partially offset by domestic stabilization policies and capital flow management [48], which reduce the sensitivity of equity volatility to external shocks.

6.3.5. Climate-Sentiment Covariance Effects (H7a-H7b)

The interaction of equity market volatility calibrated to investor sentiment and transition risk variance, $EMV_{IVS,t} \times VTR$, is positive and statistically significant. This confirms **H7a** and indicates that transition risk becomes more destabilizing when market volatility co-moves strongly with investor sentiment. In such regimes, pessimistic sentiment amplifies repricing pressures on carbon-intensive

exposures, increasing volatility through heightened risk aversion and flight-to-safety behavior.

In contrast, the interaction equity market volatility calibrated to consumer confidence and physical risk variance, $EMV_{CNS,t} \times VPR$, is negative and statistically significant, supporting **H7b**. This result indicates that stronger macro-sentiment conditions buffer the impact of physical risk variance on bank volatility. During periods of high consumer confidence, expectations of economic resilience, sustained demand, and effective disaster response reduce the perceived financial impact of physical climate shocks [58].

6.3.6. Robustness Checking

In the previous sections, liquidity was measured based on the contemporaneous relationship between LIQ_t and absolute stock return variance. However, this contemporaneous specification may introduce potential simultaneity bias because liquidity and stock return volatility may influence each other within the same period. To address this concern, this section conducts an additional robustness test by using the one-period lag of the change in liquidity, ΔLIQ_{t-1}, while retaining the other explanatory variables from the original specification. The results are reported in Table 9.

Overall, the estimates remain broadly consistent with the main findings, with only minor changes in the magnitude and significance of some coefficients. In particular, the interaction term, $EMV_{IVS,t} \times VTR_t$, remains positive and statistically significant, providing support for **H7a**. This finding suggests that transition risk tends to have a more destabilizing effect when investor sentiment interacts with market volatility and transition-related climate variance. An exception is observed for MUFG, where the result may reflect a spurious correlation or, alternatively, the effects of insulating policies adopted by the Japanese banking sector.

The positive effect is also reflected in the estimates of the interaction, $EMV_{CNS,t} \times VPR_t$, for three major U.S. banks—BOA, CITI, and JPM. This result may indicate that physical climate volatility can generate household income losses and increase the risk of stranded assets, thereby creating additional risks to bank stability.

For the non-U.S. banks, the coefficients of the interaction term, $EMV_{CNS,t} \times VPR_t$, remain negative and statistically significant and confirm **H7b.** Therefore, the possibility that the estimated relationships are primarily driven by mechanical simultaneity appears limited for these banks. The coefficients and statistical significance of the other explanatory variables, including ΔLIQ_{t-1}, are also broadly comparable with those reported in the main analysis.

Taken together, these results indicate that the main conclusions are not materially affected by replacing the contemporaneous change in liquidity with its one-period lag. The consistency of the findings provides further evidence that the relationships identified in the baseline model are robust to potential simultaneity concerns.

Table 9. Robust check of financial volatility and investor & consumer sentiments interacting with climate risk variances on G-SIB stock variances by using lagged liquidity as control variable in the GED-GARCH model.

	C	VIX_t	$EMV_{MP,t}$	Δr_t	ΔLIQ_{t-1}	$\Delta GEPU_t$	$EMV_{IVS,t} \cdot VTR_t$	$EMV_{CNS,t} \cdot VPR_t$	ω	ε_{t-1}^2	σ_{t-1}^2	$\bar{R}^2$
V_t^{BOA}	−17.794	2.001	7.856	−0.521	24.840	0.411	1.025	0.084	278.394	0.227	0.715	0.26
	−4.72	8.38	20.24	−11.59	15.12	8.97	3.24	3.14	0.40	0.51	1.08	
V_t^{CITI}	−126.224	9.066	8.908	−4.989	28.790	−0.156	1.478	0.035	184.200	0.067	0.938	0.15
	−33.20	26.31	18.77	−7.83	5.50	−3.28	2.55	36.84	0.41	0.18	5.33	
V_t^{JPM}	−24.890	2.328	4.804	−1.120	30.041	0.280	0.639	0.279	152.070	0.231	0.748	0.25
	−8.30	21.37	12.66	−2.85	7.86	6.22	7.25	3.01	0.37	0.43	1.19	
V_t^{BNP}	−30.074	3.449	10.801	−10.272	5.863	1.471	0.408	−0.337	66.654	0.204	0.785	0.26
	−4.03	10.13	9.20	−16.13	15.28	9.02	4.40	−3.03	0.32	0.21	2.44	
V_t^{DEUB}	−45.283	3.499	13.158	−8.517	6.184	1.081	2.009	−0.621	64.592	0.314	0.634	0.28
	−7.94	10.34	13.18	−8.79	18.34	9.57	4.21	−6.01	0.45	0.52	0.90	
V_t^{HSBC}	−21.948	1.881	4.536	−1.282	17.897	−0.141	0.147	−0.404	118.553	0.228	0.698	0.18
	−5.95	7.86	15.42	−2.47	4.19	−2.35	2.34	−9.92	0.39	0.40	1.922	
V_t^{MUFG}	16.720	−1.421	10.748	−2.716	16.467	−0.022	−0.166	−0.357	138.758	0.189	0.638	0.03
	3.50	−13.47	15.44	−2.94	13.57	−1.41	−0.36	−4.22	1.55	0.90	3.01	
V_t^{BOC}	33.130	−1.512	1.362	−0.088	13.966	−0.068	0.297	−0.696	151.606	0.922	0.086	0.06
	21.37	−30.04	8.95	−13.73	12.31	−2.62	2.31	−8.63	2.09	1.40	0.43	
V_t^{ABC}	22.071	−0.662	0.202	−0.980	10.244	0.134	0.367	−0.079	47.524	0.627	0.317	0.08
	25.92	−14.99	6.31	−10.73	13.12	20.26	4.18	−4.42	1.93	1.54	1.47	
V_t^{ICBC}	34.082	−0.996	0.583	−3.551	6.999	0.159	0.775	−0.122	72.105	0.882	0.052	0.09
	14.20	−9.72	4.68	−12.02	5.48	7.34	3.64	−9.44	2.26	1.86	0.40	

Notes**:** The dependent variable is bank stock variance V_t^i, where superscript i denotes Bank of America (BOA), Citigroup (CITI), JPMorgan Chase (JPM), BNP Paribas (BNP), Deutsche Bank (DEUB), HSBC Holdings (HSBC), Mitsubishi UFJ Financial Group (MUFG), Bank of China (BOC), Agricultural Bank of China (ABC), and Industrial and Commercial Bank of China (ICBC). VIX_t is the CBOE Volatility Index. Δr_t denotes changes in the short-term interest rate. $\mathrm{Cov}(\sigma_t, MP_t)$ measures the covariance between equity market volatility and monetary policy shocks. $GEPU_t$ denotes global economic policy uncertainty. LIQ_t measures stock liquidity, defined as trading volume turnover divided by the absolute value of stock returns. ΔCPU_t denotes changes in climate policy uncertainty. Δ denotes first differences of the respective variables. All volatility-related coefficients ω are scaled by 10^{-2} for presentation purposes. The interaction term $EMV_{IVS,t} \cdot VTR_t$ and $EMV_{IVS,t} \cdot VPR_t$ denote the equity market volatility calibrated to investor sentiment times transition risk variance (VTR_t) and physical risk variance (VPR_t). The slopes of interaction coefficients are scaled by 10^{-3} for presentation purposes. Reported values in the first row are estimated coefficients; the second row reports z-statistics. Statistical significance is based on standard normal critical values of 2.63, 1.98, and 1.66 at the 1%, 5%, and 10% levels, respectively.

7. Conclusion and Implications

7.1. Summary of Findings

This paper provides systematic evidence on how climate risk affects bank stock volatility in a heterogeneous and sentiment-dependent manner for globally systemically important banks (G-SIBs). The results point to four key conclusions. First, traditional macro-financial uncertainty remains a dominant driver of bank stock volatility. Measures such as the VIX and related uncertainty indicators exert strong and statistically significant effects on bank equity volatility. This finding confirms that global financial conditions continue to play a central role in shaping bank risk, even in the presence of emerging climate-related risk factors.

Second, climate risk exhibits a clear and robust asymmetry across its two fundamental dimensions. Transition risk variance increases bank stock volatility, while physical risk variance reduces it. This divergence reflects fundamentally different risk-generation mechanisms. Transition risk is driven by policy uncertainty, technological disruption, and valuation repricing under Knightian uncertainty, which amplifies instability in expectations. In contrast, physical risk is increasingly characterized by partial predictability, insurance coverage, and adaptive responses that reduce its marginal contribution to financial volatility.

Third, the transmission of climate risk is strongly state-dependent on sentiment conditions. Consumer confidence amplifies the impact of transition risk on bank volatility but attenuates the effect of physical risk. This indicates that sentiment does not operate as a uniform stabilizing or destabilizing force; instead, its effect depends on the nature of the underlying climate risk. Optimistic sentiment increases sensitivity to policy-driven uncertainty, while simultaneously reinforcing perceptions of resilience against physical shocks.

Fourth, these sentiment-dependent effects are reinforced by broader macro-financial regimes. The interaction between market volatility-sentiment co-movement and transition risk amplifies bank stock volatility, whereas the corresponding interaction with physical risk dampens volatility. This evidence highlights that climate risk transmission is jointly shaped by risk type and the prevailing configuration of market fear, policy response, and sentiment dynamics.

Overall, the findings demonstrate that climate risk is not a homogeneous driver of financial instability. Instead, its effects depend critically on whether it operates through expectation-driven valuation channels (transition risk) or through loss-and-resilience channels (physical risk), the U.S. banks vs. non-U.S. banks, and on how these channels interact with macro-financial sentiment regimes.

7.2. Policy Implications

These results have three main implications for regulators and risk managers. First, climate stress testing frameworks should explicitly differentiate between transition and physical risk rather than treating climate exposure as a single aggregate factor. In particular, transition risk monitoring should incorporate sentiment and volatility conditions, as its destabilizing effects are significantly stronger during

periods of heightened market sensitivity.

Second, macroprudential policy design should account for the buffering role of consumer confidence in physical risk transmission. Policies that support economic stability and household confidence may indirectly strengthen the resilience of the banking sector to climate-related physical shocks.

Third, bank risk management systems should integrate sentiment indicators into climate risk models. The evidence suggests that climate risk does not materialize independently of market psychology; instead, its financial impact is amplified or dampened depending on prevailing sentiment conditions and volatility regimes.

7.3. Future Research Directions

Several avenues for future research emerge from this study. First, future work could refine climate risk measurement by incorporating physical exposure data from satellite observations, geospatial datasets, or loan-level climate vulnerability indicators. Second, extending the analysis beyond G-SIBs would help assess whether the observed asymmetry holds for smaller and less diversified banking institutions. Third, further research could examine portfolio-level heterogeneity by distinguishing between green and carbon-intensive lending exposures within banks. Finally, this study does not explicitly model potential nonlinearities or threshold effects. It is possible that the stabilizing role of physical risk reverses once climate damages exceed adaptation capacity, potentially transforming idiosyncratic shocks into systemic risk events. Exploring such nonlinear regimes would be particularly valuable for future climate stress testing frameworks.

7.4. Concluding Remarks

Climate change is reshaping financial stability, but its effects are structurally asymmetric rather than uniform. This paper shows that transition risk amplifies bank stock volatility through policy uncertainty and expectation revision, while physical risk tends to reduce volatility through adaptation, insurance, and increasing predictability. Importantly, these effects are not constant: they vary systematically with sentiment and macro-financial regimes.

The central implication is that climate risk cannot be understood independently of market psychology and macro-financial conditions. For regulators and financial institutions, this requires moving beyond aggregate climate exposure measures toward frameworks that explicitly incorporate risk heterogeneity and sentiment-state dependence. The transition to a low-carbon economy will, therefore, not only reshape credit allocation but also redefine the volatility dynamics of the global banking system.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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