Does Climate-Induced Liquidity Stress Amplify Due to Asymmetric Macro Effects?

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Abstract:

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This study examines the impact of climate risk damage on bank liquidity using a panel of 560 U.S. commercial banks over 55 quarters (2010–2023). Using a dynamic two-way fixed-effects model, we identify a significant negative relationship between physical climate damage and liquidity. The Interaction analysis indicates that macroeconomic conditions act as force multipliers, nonlinearly intensifying climate-risk-induced vulnerability.

The results further show that elevated inflation and tightening of monetary policy can significantly endogenously amplify the liquidity stress on banks. We identify that compounded liquidity and macroeconomic stress, whereby climate shocks increase the internal liquidity demand while higher interest rates raise external funding costs and constrain recovery. These findings highlight how a macro climate amplification effect can endogenously affect small and medium banks more significantly, exhibiting a negative sensitivity to climate risk and a persistent negative liquidity coefficient compared to large banks. The results underscore the need for central banks to integrate climate risk into macroprudential and stress testing frameworks, particularly for small and medium banks during periods of monetary tightening.

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1. Introduction

Climate risks are a significant green swan risk to banks' financial stability, impacting balance sheets by depreciating asset values and resulting in liquidity stress. It is imperative for banks to proactively forecast and take preventive measures to mitigate the likelihood of these material risks' impact on the wider global financial system. Extreme climate damage caused by natural disasters is increasingly affecting households and asset valuations, posing systemic risk transmission to banks' risk exposure (Batten et al., 2016; Battiston et al., 2016; Dafermos et al., 2017; Faiella et al., 2022). The macroeconomic environment post the Global Financial Crisis has been predominantly characterised by a prolonged low-inflation and low-interest-rate regime. However, the recent monetary policy tightening by the Federal Reserve, coupled with the intensifying climate risk damage, raises concerns that this may compound into a liquidity stress on banks (Acharya et al., 2023).

To address this gap, we explore how climate shocks result in liquidity stress and are further amplified during high inflation and monetary policy regimes that adversely affect the liquidity of U.S. commercial banks. We study a panel of 560 U.S. commercial banks over the period 2010–2023 and employ a dynamic two-way fixed effects model with clustered standard errors. The study documents a robust negative relationship between physical climate damage and U.S. banks' liquidity. We provide empirical evidence that physical climate risk damage-induced liquidity stress is significantly amplified during periods of elevated inflation and interest rate regimes. The study highlights that the impact of climate risk and liquidity stress is

compounded by the indirect endogenous macro amplifier transmission channels that can potentially cascade through the broader financial system.

Our findings suggest that the relationship between climate-induced liquidity risk and macro amplifiers is non-linear and state-dependent. As evidenced by the lagged liquidity coefficient ($\beta \approx 0.88$), banks exhibit significant contraction in their liquidity creation. This structural severity during periods of stress is well-supported by the existing frameworks (Berger & Bouwman, 2009; Diamond & Rajan, 2001) . Our study further identifies an indirect endogenous feedback loop where macroeconomic conditions act as amplifiers, adversely impacting banks' liquidity. We observe a significant negative interaction between climate risk damage and interest rate regimes, which is consistent with the findings of (Bernanke et al., 1999). The results also demonstrate that tighter monetary policy regimes intensify shock transmission through endogenous amplification mechanisms.

This study makes the following significant contributions to the extant literature related to climate risk and bank liquidity. First, the study contributes primarily by extending the Financial Accelerator theory, by discovering climate stress-induced macro amplification as a novel transmission channel that can exacerbate the risk exposure of banks. Secondly, we move beyond direct-effect models of climate risk to identify a macro-climate mechanism that is state-dependent. We demonstrate that inflationary pressures and restrictive monetary policy act as significant amplifiers of climate-induced liquidity shocks. While both climate shocks and macroeconomic variables are exogenous to banks, their interaction generates an indirect endogenous amplification mechanism within the financial system. The amplification effect is more pronounced for small and medium banks that hold fewer high-quality assets and lack access to global markets.

The remainder of the paper is structured as follows: Section 2 describes the extant Literature, Section 3 the Research Design, Section 4 presents the empirical results, including

the baseline, interaction effects, robustness, heterogeneity, and further analysis. Section 5 concludes the paper.

2. Literature Review

The transmission of physical climate risk to bank liquidity is fundamentally based on the Financial Accelerator Theory (Bernanke et al., 1999), which posits that endogenous growth in credit markets can significantly amplify the impact of exogenous shocks. As aligned with the Financial Fragility Theory (Diamond & Dybvig, 1983), banks are susceptible to unexpected liquidity drains due to deposit runs caused by the physical damages of climate disasters, thus leading to liquidity stress. The impact of a physical climate risk damage on a bank and its subsequent response depends on the liquidity of its assets and the monetary policy environment (Schüwer et al., 2019). A bank holding low-liquidity assets during an exogenous climate shock, along with a contractionary monetary policy, can significantly amplify the risk. Further, in a high-interest-rate environment, the cost of the interbank short-term lending rate will become expensive, and this adversely impacts the financial markets as a secondary source of liquidity is constrained. This creates a macro financial amplification channel due to the exogenous climate shock triggers and demand for liquidity. While the indirect effect of the endogenous feedback due to restrictive monetary policy further exacerbates banks' liquidity.

Recent literature primarily examines only the exogenous implications of climate risk on bank portfolios, and focuses on its impact on credit risk and liquidity creation (Lee et al., 2022; Nieto, 2019). However, relatively limited attention has been paid to investigating how climate shocks can also endogenously affect bank liquidity, especially under varying macroeconomic regimes. Inflation and interest rates may act as amplification channels during

climate shocks, thereby intensifying the impact on banks' profitability by increasing credit default risk and affecting banks' liquidity creation (Lang et al., 2023; Lee et al., 2022b).

As these are pivotal climate macro interactions, there is a probability that banks' forecasting models may run the risk of understating the true liquidity implications of climate risk impact. This gap is critical to address, as liquidity is a critical buffer for banks against both idiosyncratic and systemic stress (Diamond & Dybvig, 1983; Zhang et al., 2021). We hence explore the following research questions: How do aggregate climate damage events directly impact the liquidity positions of U.S. commercial banks? Does an inflationary macroeconomic environment amplify the liquidity shocks induced by aggregate climate risk? How does the prevailing monetary policy and interest rate environment interact with climate risk to amplify bank liquidity stress?

3. Research Design

3.1 Sample and data

Our sample is derived from the bank-level financial data obtained from the FFIEC Call Report Data (CDR) filings, covering a large sample of commercial banks over the period 2010–2023. The panel consists of 560 banks observed quarterly, yielding approximately 30,800 bank–quarter observations. To mitigate the influence of extreme observations, the liquidity variable and its lag are winsorized. We focus on banks with consistent reporting over the sample period to ensure comparability and reduce noise from entry and exit.

To identify exogenous physical shocks, we utilise high-impact climate damage from the National Oceanic and Atmospheric Administration (NOAA) National Centres for Environmental Information (NCEI) Billion-Dollar Weather and Climate Disasters database, which tracks economically significant disasters across the United States from 2010 to 2023.

We also use the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis for the Consumer Price Index (CPI) and the Effective Federal Funds Rate (EFFR).

3.2. Econometric model

To examine the impact of climate risk on bank liquidity, we design the following dynamic two-way fixed effects panel model:

$$\text{Liquidity}_{i,t} = \alpha + \rho\text{Liquidity}_{i,t-1} + \beta_1\text{ClimateDamage}_t + \beta_2\text{Log(TotalAssets)}_{i,t} + \mu_i + \tau_y + \epsilon_{i,t} \quad (1)$$

Note: Equation 1 estimates the baseline direct effect of climate risk, where the primary coefficient of interest, β_1, captures how aggregate quarter-to-quarter climate damage independently impacts bank liquidity.

Variable Definitions

Liquidity_i,t: The liquidity metric for bank i in quarter t.
Liquidity_$i,t-1$: The one-quarter lagged liquidity metric for bank i.
ClimateDamage_t: The aggregate climate damage in quarter t, applied uniformly across all banks in the sample.
$\text{Log(TotalAssets)}_{i,t}$: The natural logarithm of total assets for bank i in quarter t, controlling for continuous changes in bank size.
μ_i: Bank (entity) fixed effects, capturing time-invariant, unobserved characteristics unique to each bank.
τ_y: Year fixed effects (where y is the specific year corresponding to quarter t), absorbing broader annual macroeconomic trends.
$\epsilon_{i,t}$: The idiosyncratic error term.

Where i indexes banks and t denotes time (year). Considering the dynamic longitudinal panel set up, we estimate the baseline model using fixed-effects panel least squares with clustered standard errors at the bank level. Following the banking literature, we estimate fixed-effects panel regressions with standard errors clustered at the bank level to account for within-bank correlation (e.g., Gatev and Strahan, 2006; Kashyap et al., 2002), when the emphasis is on within-bank dynamics and the regressors of interest are plausibly exogenous. This approach

thus controls for unobserved bank-specific heterogeneity while accounting for within-bank serial correlation and heteroskedasticity (Petersen, 2009; Kashyap et al., 2002; Gatev and Strahan, 2006).

The dependent variable, $\text{Liquidity}_{i,t}$, represents the liquidity position of the bank i at time t. The inclusion of the lagged dependent variable, $\text{Liquidity}_{i,t-1}$, captures persistence in the bank's liquidity to account for dynamic persistence in banks' liquidity profile. The key explanatory variable, $\text{ClimateDamageCount}_{i,t}$, measures the bank-level exposure to climate-related damage. The bank size is controlled for using $\text{LogTotalAssets}_{i,t}$, defined as the natural logarithm of total assets. We take the natural logarithm of the total assets of banks to normalise the highly right-skewed distribution of bank sizes across our sample and reduce heteroskedasticity. This helps to control for bank size-related heterogeneity in liquidity management dimension. This transformation ensures that the variable captures proportional differences in scale rather than absolute dollar variations.

Further, to account for time-specific effects and macroeconomic shocks, we introduce a full set of year dummy variables (YearDummy_t). We include year dummies to absorb the unobserved, aggregate macroeconomic shocks and regulatory changes that affect all banks simultaneously in any given year. This ensures that our model isolates the immediate, quarter-to-quarter impact of climate shocks rather than capturing broader annual economic trends. The bank-specific unobserved heterogeneity is controlled through bank fixed effects (μ_i), that absorbs time-invariant institutional characteristics, while year dummies capture aggregate macroeconomic and regulatory shocks common to all banks in a given period. The $\varepsilon_{i,t}$represents the idiosyncratic error term.

All variables used in the empirical analysis are defined in detail in **Table A1**. The model is estimated using a panel fixed effects approach with clustered standard errors to address

potential heteroskedasticity and serial correlation. The empirical analysis is conducted using Python.

4. Results

4.1 Baseline effect

Table 1 displays the baseline estimation results of the impact of climate damage on banks' liquidity. The coefficient of Climate Damage impact is observed to be negative and significant at 5% level (p = 0.0447). Results confirm, that physical climate risks exert an immediate contractionary pressure on bank liquid reserves. indicating that higher exposure to physical climate shocks is associated with a decline in bank liquidity. This further demonstrates that climate disasters trigger a dual strain via dual channels: we observe an immediate outflow of cash as depositors seek emergency funding (the funding liquidity channel) and a potential impairment of liquid assets (the market liquidity channel). While the coefficient appears small in absolute terms, it represents a significant change in the liquidity ratio across a panel of 560 banks. Specifically, these results indicate that climate shocks act as a persistent drain on the high-quality liquid assets (HQLA) that banks maintain as a buffer against idiosyncratic shocks.

The coefficient on lagged liquidity is positive and highly significant ($\beta = 0.887$, $t = 118.96$), indicating strong persistence in the bank's liquidity positions over time. This highlights that climate risk damage results in persistent liquidity impact, which impacts the long-term liquidity of banks and further constrains liquidity creation.

The coefficient on climate damage is negative and statistically significant at the 5% level ($\beta = -6.88$, $t = -2.07$), suggesting that greater exposure to climate-related damage is associated with reduced bank liquidity. Bank size, which is proxied by the logarithm of total assets, exhibits a positive and significant effect ($\beta = 0.0053$, $t = 4.04$), implying that larger banks tend to maintain higher liquidity levels. The model includes year dummies and bank

fixed effects, with a within $R^2$of 0.822, indicates that the model captures a substantial proportion of the variation in liquidity over time within banks. A clustered standard error approach has been applied to account for within-bank serial correlation and heteroskedastic error terms.

Table 1
Baseline Results: Climate Risk and Bank Liquidity

Variables	**(1)** *Liquidity*
Panel A: Core regressors	**Coefficient**
Lagged liquidity (Liqt−1)	0.8870*** (118.96)
Log total assets	0.0053*** (4.044)
Panel B: Climate risk	
Climate damage total	−6.888 × 10−6** (−2.008)
Panel C: Selected year fixed effects	
2011	0.0034*** (3.763)
2013	−0.0072*** (−7.958)
2016	−0.0115*** (−11.225)
2018	−0.0133*** (−11.337)
2021	0.0072*** (4.350)
2022	−0.0237*** (−13.620)
2023	−0.0153*** (−9.206)
Remaining year dummies	Included

Panel D: Model diagnostics	
Year dummies	Yes
Bank fixed effects	Yes
Observations	30,800
Banks	560
Time periods	55
R^2 (within)	0.8226
R^2 (between)	0.9827
R^2 (overall)	0.9461

Notes: This table reports Panel OLS estimates with two-way fixed effects. The dependent variable is the winsorised liquidity ratio (*liquidity_w*). The baseline specification employs climate damage total as the primary climate risk regressor, measuring the aggregate economic severity of quarterly climate damage in billions of USD. Bank fixed effects absorb time-invariant institutional heterogeneity. Year dummies capture aggregate macroeconomic shocks common to all banks in a given year. Only economically significant year fixed effect coefficients are reported for brevity; full estimates are available upon request. Clustered t-statistics are reported in parentheses, with standard errors clustered at the entity (bank) level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. F-test for poolability: F(559, 30224) = 3.392, p = 0.000.

4.2 Robustness check

4.2.1. Robustness Check: Placebo Test via Random Permutation

We next conduct an empirical validation to ensure that the baseline results and the initial causal identification are robust. A nonparametric placebo simulation is run to mitigate potential biases arising from unobserved time-invariant movements and outliers. A significant methodological concern in panel-based climate risk arises from spurious inference of idiosyncratic statistical characteristics of the underlying data.

To address the above challenges, we adopt the stochastic permutation approach of (Hagemann, 2019), whereby we artificially decouple the economic transmission mechanism linking the exogenous shock to U.S. banks' balance sheets. Specifically, we randomly reassign the actual climate risk variable (climate_effr) across the panel 500 times. This iterative procedure breaks the causal link between specific climate damage and contemporaneous bank liquidity, while meticulously preserving the particular statistical instants of the climate variable and the underlying structure of the banks and time fixed effects.

As illustrated in **Fig.1,** the results of this Monte Carlo simulation provide compelling evidence for the robustness of our baseline model. The empirical null distribution generated by the 500 permuted placebo shocks is approximately normal, and the coefficients are centred around zero. This confirms that randomly assigned climate damage exerts no systematic influence, confirming that our main results are robust. This extreme left-tail positioning provides definitive empirical verification that the documented liquidity drain is structurally driven by specifically identified climate risk frictions, rather than a stochastic artefact of the panel design.

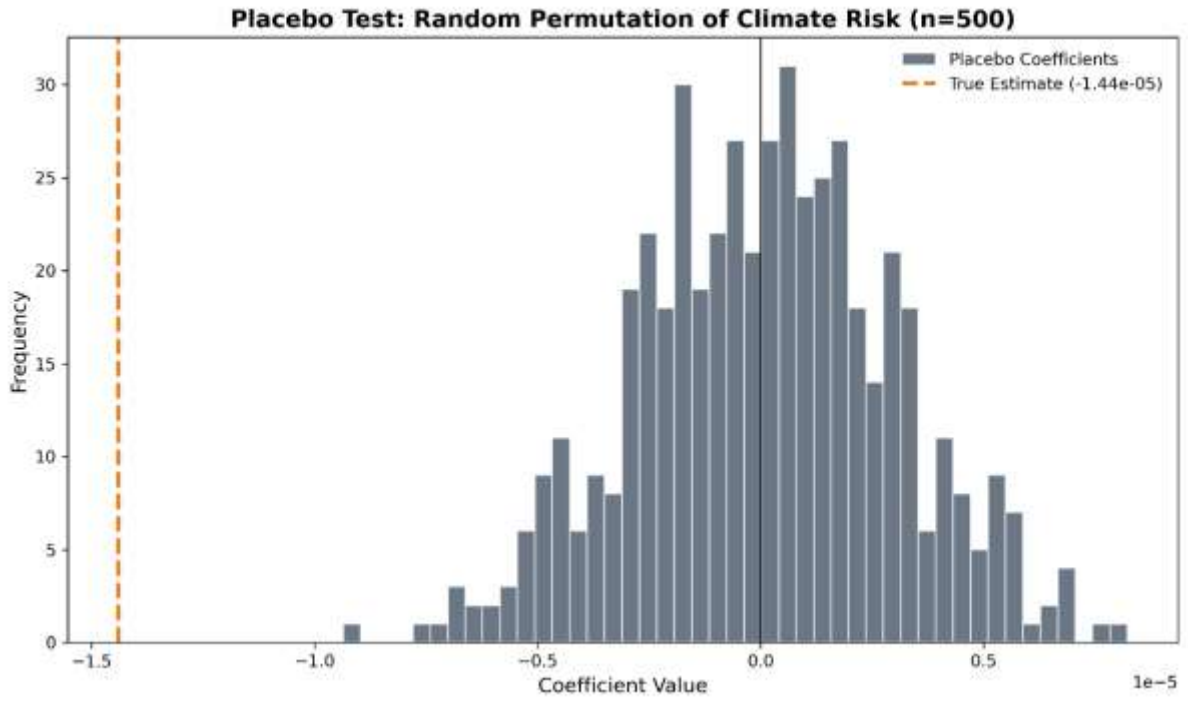


Fig. 1. Monte Carlo Simulation via random permutation
Note: The figure presents the distribution of placebo coefficients obtained from 500 random permutations of the climate risk variable. The placebo coefficients are centred around zero. The dashed vertical line indicates the true estimated coefficient of the extreme left tail of the distribution, indicating that the observed effect is statistically unlikely to arise by chance.

4.3 Amplification Effects: Role of Macroeconomic Environment

As the baseline results establish a strong negative impact of climate risk on the bank's liquidity, which aligns with the extant literature (Krueger et al., 2020; Lee et al., 2022)**.** We extend the

extant literature by documenting that the deleterious effect of climate risk on bank liquidity is endogenously magnified via indirect macroeconomic transmission mechanisms, thereby amplifying systemic pressures on the banking sector**.** To interrogate the macroeconomic amplification mechanism, we augment the baseline two-way fixed effects panel specification with regime-contingent interaction terms. This facilitates identification of two distinct amplification pathways: (i) whether high inflation regimes compound the deleterious effect of climate risk on bank liquidity, and (ii) whether contractionary monetary policy environments exacerbate the climate risk–liquidity nexus.

4.2.1 Macro Amplifier Channel Effects Analysis

The results in **Table 2** provide evidence of a macroeconomic amplification channel, with negative and statistically significant interaction effects indicating that the adverse impact of climate risk is exacerbated during periods of elevated inflation and restrictive monetary policy. The interaction specification allows for state-dependent effects to capture how the transmission of climate shocks varies with inflation and monetary policy conditions.

The findings provide evidence of state-dependent effects, whereby the macroeconomic environment conditions amplify to result in the endogenous transmission of climate shocks to bank liquidity. The interaction results support the presence of compounded liquidity and funding stress. Climate shocks increase internal liquidity demand through precautionary motives, while higher interest rates act in tandem to raise the cost of external funding. This dual stress constrains banks' ability to replenish liquidity, resulting in a more pronounced and persistent decline in liquidity positions for an elongated time period.

Importantly, these dynamics are consistent with an endogenous amplification mechanism, whereby the initial impact of an exogenous climate shock is magnified by prevailing macro-financial conditions. The results suggest that inflation and monetary

tightening act as endogenous amplifiers, causing nonlinear effects that intensify banks' exposure to climate risk. The amplification effects of macroeconomic conditions on climate risk, **Table 2**, highlight a structural vulnerability in bank lending. When physical climate shocks coincide with adverse shifts in interest rates, banks exhibit liquidity hysteresis (Dow et al., 2021), wherein the temporary tightening of credit conditions translates into a persistent contraction of liquidity creation, a mechanism consistent with the credit supply dynamics documented by (Cornett et al., 2011) and (Berger & Bouwman, 2017), who establish that liquidity shocks arising from adverse macro conditions generate enduring impairments in banks' balance sheet capacity.

4.3 Inflation and Monetary tightening as an amplification channel

When interacting climate risk with inflation, the results reveal that the deleterious effect of climate risk on bank liquidity is significantly amplified during high inflation regimes. This suggests that inflation exacerbates climate-induced liquidity stress, likely by eroding real asset values and elevating funding costs. This is consistent with evidence that inflationary environments generate deposit outflows that constrain banks' liquidity creation capacity (Drechsler et al., 2017) and impair balance sheet resilience (Cornett et al., 2011).

The amplification effect between climate risk and interest rates yields a negative and highly significant coefficient, indicating that monetary tightening amplifies the liquidity impact of climate shocks. Higher interest rates increase funding costs and reduce the market value of bank assets (Jiang et al., 2024) document that monetary tightening reduced U.S. banks' mark-to-market asset values by an average of 10%, while (Brunnermeier & Pedersen, 2009) establish that tightening funding conditions and declining asset values are mutually reinforcing, thereby exacerbating liquidity pressures following climate damage. This result is consonant with the financial accelerator mechanism of (Bernanke et al., 1999), wherein restrictive monetary

conditions endogenously amplify the transmission of climate risk to bank liquidity through self-reinforcing macro-financial feedback, rather than merely adding an additive shock.

Model 2 (Climate and CPI Amplification Interaction)

$$\text{Liquidity}_{i,t} = \alpha + \rho\text{Liquidity}_{i,t-1} + \beta_1(\text{Climate} \times \text{CPI})_t + \beta_2\text{Log}(\text{TotalAssets})_{i,t} + \mu_i + \tau_y + \epsilon_{i,t} \quad (2)$$

Note: Equation 2 estimates the amplification effect of inflation, where the primary coefficient of interest, β_1, captures the extent to which the Consumer Price Index (CPI) exacerbates climate-induced liquidity stress.

Model 3 (Climate and Interest Rate Amplification Interaction)

$$\text{Liquidity}_{i,t} = \alpha + \rho\text{Liquidity}_{i,t-1} + \beta_1(\text{Climate} \times \text{EEFR})_t + \beta_2\text{Log}(\text{TotalAssets})_{i,t} + \mu_i + \tau_y + \epsilon_{i,t} \quad (3)$$

Note: Equation 3 estimates the amplification effect of the interest rate environment, where β_1 captures how the Effective Federal Funds Rate (EEFR) compounds climate-induced liquidity stress.

Variable Definitions:

Liquidity_i,t: The liquidity metric for bank *i* in quarter *t*.
Liquidity_i,t-1: The one-quarter lagged liquidity metric for bank *i*.
ClimateDamage_t: The aggregate climate damage in quarter *t*, applied uniformly across all banks in the sample.
ln(TotalAssets_i,t): The natural logarithm of total assets for bank *i* in quarter *t*, controlling for continuous changes in bank size.
(ClimateDamage × CPI)_t: The interaction term between aggregate climate damage and the Consumer Price Index (inflation) in quarter *t*.
(ClimateDamage × EEFR)_t: The interaction term between aggregate climate damage and the Effective Federal Funds Rate in quarter *t*.
μ_i: Bank (entity) fixed effects, capturing time-invariant, unobserved characteristics unique to each bank.
τ_y: Year fixed effects (where *y* is the specific year corresponding to quarter *t*), absorbing broader annual macroeconomic trends.
ε_i,t: The idiosyncratic error term.

Climate Risk and Macro Amplification Effects

Table 2

Macroeconomic Amplification of Climate Risk on Bank Liquidity

Variables	**(2)** *Climate × CPI*	**(3)** *Climate × EFFR*
Panel A: Core regressors		
Lagged liquidity (Liqt−1)	0.8871***	0.8868***
	(118.95)	(118.79)
Log total assets	0.0053***	0.0053***
	(4.049)	(4.040)
Panel B: Composite climate stress measures		
Climate × CPI	−1.485 × 10−5***	—
	(−2.713)	
Climate × EFFR	—	−1.365 × 10−5***
		(−5.248)
Panel C: Selected year fixed effects		
2011	0.0036***	0.0033***
	(3.962)	(3.643)
2013	−0.0072***	−0.0072***
	(−7.973)	(−7.973)
2016	−0.0115***	−0.0115***
	(−11.205)	(−11.221)
2018	−0.0133***	−0.0127***
	(−11.312)	(−10.821)
2021	0.0079***	0.0070***
	(4.702)	(4.212)
2022	−0.0229***	−0.0228***
	(−12.949)	(−12.961)
2023	−0.0152***	−0.0139***
	(−9.119)	(−8.245)
Remaining year dummies	Included	Included
Panel D: Model diagnostics		
Year dummies	Yes	Yes
Bank fixed effects	Yes	Yes
Observations	30,800	30,800

Banks	560	560
Time periods	55	55
R^2 (within)	0.8227	0.8227
R^2 (between)	0.9827	0.9826
R^2 (overall)	0.9461	0.9461

N*otes:* This table reports Panel OLS estimates with two-way fixed effects for the macroeconomic amplification channel models. The dependent variable is the winsorised liquidity ratio (*liquidity_w*). Model (2) introduces Climate × CPI, a composite climate stress measure capturing the joint exposure of banks to climate damage under inflationary conditions, constructed as the product of *climate_damage_total* and the quarterly rate of change in the Consumer Price Index. Model (3) introduces Climate × EFFR, capturing climate damage severity under restrictive monetary policy regimes, constructed as the product of *climate_damage_total* and the effective federal funds rate. Bank fixed effects absorb time-invariant institutional heterogeneity. Year dummies capture aggregate macroeconomic shocks common to all banks. Only economically significant year fixed effect coefficients are reported; full estimates available upon request. Clustered t-statistics in parentheses; standard errors clustered at the entity (bank) level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.4 Robustness Check: Time-Subsample and Crisis Exclusion

A critical concern in panel data estimation encompassing the 2020-2021 period is the potential for temporal confounding due to the COVID-19 pandemic. To ensure our baseline estimates are not capturing the idiosyncratic volatility of this crisis, we conduct a time-subsample robustness test by explicitly excluding the 2020 and 2021 observations from our panel data.

A re-examination of the baseline fixed-effects model on this non-crisis subsample yields results that are highly consistent with the initial results. The coefficient on climate_effr remains negative and quantitatively stable (−1.431e−05 compared to −1.44e−05 in the baseline), and continues to be statistically significant at the 1% level (p = 0.000), confirming the robustness of the results.

4.5. Further Analysis: Structural Heterogeneity in Liquidity Transmission

The baseline estimates potentially mask significant **s**ize-dependent asymmetries in the transmission of climate-driven shocks to bank balance sheets. Following the bank heterogeneity and balance sheet channel literature (Kashyap et al., 2002; Kashyap & Stein, 2000) we partition the sample into Small (N=349), Medium (N=202), and Large (N=9) cohorts to examine the role of institutional scale in absorbing exogenous risk. Our results reveal a

"sensitivity gradient" where smaller banks exhibit a disproportionate vulnerability to climate_effr. For Small banks, the coefficient is highly significant ($\beta = -1.44 \times 10^{-5}$, $p < 0.01$\$), supporting the Asset-Liability Correlation Channel. In the absence of diversified funding streams, these banks face high Liquidity Persistence ($Liqt - 1 = 0.8817$), indicating a structural rigidity. When a climate damage occurs, the resulting idiosyncratic shock simultaneously impairs the bank's underlying collateral and triggers a drain on its concentrated deposit base, a phenomenon theoretically described as "Funding Market Segmentation" (Diamond & Rajan, 2001)

In contrast, our findings for large banks indicate a resilience effect. For this cohort, the impact of climate_effr remains statistically insignificant ($p = 0.3007$). This decoupling is consistent with the internal capital market channel, wherein systemic institutions utilize their vast resource pools to reallocate liquidity internally, effectively shielding their aggregate position from localized shocks (Correa et al., 2025). Furthermore, the highly significant positive coefficient for log_total_assets (beta = 0.0542, $p < 0.01$) in the large-bank model confirms that for G-SIBs, absolute size acts as a liquidity buffer, facilitated by their access to broader wholesale markets and the stringent High-Quality Liquid Asset (HQLA) requirements of the Basel III framework (Kovner & Van Tassel, 2022). This provides evidence that climate risk acts as an asymmetric friction, primarily affecting the liquidity stability of institutions with lower funding elasticity.

Table 3: Comparative Analysis of Liquidity Transmission Channels

This table compares the empirical results across bank cohorts to assess the amplification effect on Small, Medium and Large U.S. commercial banks.

Table 3: Bank Heterogeneity Analysis — Liquidity Regression by Bank Size

Variable	Small Banks	Medium Banks	Large Banks
	(1)	*(2)*	*(3)*
Panel A: Core Regressors			
Intercept	-0.040805* (0.021466)	-0.015552 (0.030955)	-0.788867** (0.305328)
Liquidity (t−1)	0.881729*** (0.009498)	0.896968*** (0.011886)	0.741956*** (0.054941)
Climate × EFFR	-0.000014*** (3.360e-6)	-0.000012*** (4.255e-6)	-0.000013 (0.000012)
Log Total Assets	0.005788*** (0.001608)	0.003173 (0.002148)	0.054164*** (0.019587)
Panel B: Year Fixed Effects (Base Year = 2010)			
2011	0.004712*** (0.001119)	0.001105 (0.001504)	-0.000858 (0.005230)
2012	0.000164 (0.001272)	-0.003338** (0.001443)	-0.008650** (0.003884)
2013	-0.005732*** (0.001118)	-0.008732*** (0.001485)	-0.033968*** (0.012202)
2014	-0.007074*** (0.001162)	-0.010863*** (0.001461)	-0.033054*** (0.009837)
2015	-0.008803*** (0.001197)	-0.010083*** (0.001668)	-0.039167*** (0.010355)
2016	-0.010526*** (0.001280)	-0.012415*** (0.001718)	-0.041513*** (0.012406)
2017	-0.008408*** (0.001364)	-0.010493*** (0.001933)	-0.048688*** (0.013639)
2018	-0.011911*** (0.001438)	-0.012745*** (0.002049)	-0.055331*** (0.013680)
2019	-0.010133*** (0.001573)	-0.009593*** (0.002192)	-0.067462*** (0.019064)
2020	0.000973 (0.001831)	0.001871 (0.002485)	-0.031026** (0.012845)
2021	0.008439*** (0.002107)	0.006237** (0.002723)	-0.036148** (0.016149)
2022	-0.021007*** (0.002018)	-0.024413*** (0.003386)	-0.060160*** (0.011887)
2023	-0.013199*** (0.002015)	-0.013333*** (0.002991)	-0.061079*** (0.017166)

Notes: This table reports panel regression estimates for the heterogeneity analysis by bank size. Banks are classified as Small (total assets < 25th percentile), Medium (25th–75th percentile), and Large (total assets > 75th percentile). The dependent variable is bank-level liquidity. liquidity_l1 denotes the one-period lagged dependent variable. climate_effr is the interaction between the climate risk index and the Effective Federal Funds Rate (EFFR), capturing the moderating role of monetary policy tightening on climate-driven liquidity stress. log_total_assets is the natural logarithm of total assets. Year dummies are included with 2010 as the base year. Standard errors are reported in parentheses. Columns (1)–(3) correspond to Small, Medium, and Large bank sub-samples, respectively.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

5. Conclusion

Our findings have important implications for financial stability and policy of banks across developed and developing economies. First, they suggest that climate risk poses a direct threat to bank liquidity, reinforcing concerns that climate change may undermine financial resilience. Second, the amplification effects of inflation and interest rates imply that climate risk is not constant over time but varies with macroeconomic conditions. A high inflation regime and monetary tightening are particularly risky, as climate shocks can trigger disproportionate liquidity stress.

As for regulators and Central banks, these results highlight the need to incorporate macro-financial conditions into climate stress testing frameworks. Ignoring the amplification effects between climate risk and monetary policy may underestimate systemic vulnerabilities. For banks, the findings underscore the importance of proactive liquidity management and climate risk assessment, especially in tightening monetary environments.

By integrating climate risk into a dynamic bank liquidity adjustment framework, our study contributes to the emerging literature on climate-related financial risks and macro-financial amplification. The results suggest that climate risk and macroeconomic conditions jointly determine banks' liquidity resilience, with important implications for climate policy and risk management.

Future research could explore bank-specific exposure measures or extend the analysis to other financial markets. Nevertheless, our findings provide valuable evidence on the macro-financial dimensions of climate risk impact on the liquidity of the banking sector.

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Appendix

Table A1

Variable Name	Symbol	Description
Liquidity	$\text{Liquidity}_{i,t}$	Measure of firm i's liquidity position at time t (dependent variable)
Lagged Liquidity	$\text{Liquidity}_{i,t-1}$	One-period lag of liquidity, capturing persistence in liquidity dynamics
Climate Damage Count	$\text{ClimateDamageCount}_{i,t}$	Number of climate-related damage affecting firm i at time t, proxying climate risk exposure
Firm Size	$\text{LogTotalAssets}_{i,t}$	Natural logarithm of total assets, used to control for firm size effects
Year Dummies	YearDummy_{t}	Set of dummy variables equal to 1 for each year t, capturing time-specific effects
Firm Fixed Effects	μ_i	Unobserved, time-invariant firm-specific heterogeneity
Error Term	$\varepsilon_{i,t}$	Idiosyncratic error term capturing unexplained variation

Note: This table defines all variables used in the analysis. $i$and $t$denote firm and year, respectively. Liquidity is the dependent variable. Climate risk is proxied by the frequency of climate damage, and bank size is measured by the logarithm of total assets. Year dummies and firm fixed effects are included to control for time and unobserved heterogeneity.

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Conflict of Interest

The author does not have any conflicts of interest to disclose that they may be aware of.