# Climate Risk and Bank Liquidity Creation in MENA Region: A Dual Threshold–Quantile Approach

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# Climate Risk and Bank Liquidity Creation in MENA Region: A Dual Threshold–Quantile Approach[1]

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## Abstract

This study investigates the relationship between climate risk and bank liquidity creation (LC) in MENA using a dual threshold–quantile method, complimented by a quantile-on-quantile approach. Using data from 126 banks in 19 MENA countries over the period 2006–2022, we find that climate risk has a positive effect on LC only above a certain threshold. Furthermore, this effect shows heterogeneity, varying across different levels of both climate risk and LC. Our findings contribute to the literature by providing empirical evidence on the complex interplay between climate risk and banking liquidity under varying economic conditions.



**Keywords**: Climate risk, bank liquidity creation, threshold effects, quantile regression, MENA region.

**JEL Classification** — C21, C24

## 1. Introduction

The severity and the increasing frequency of climate-related events have intensified concerns regarding their implications for economic and financial stability. Climate risk has emerged as a pivotal determinant of resilience in financial systems, particularly in regions such as the Middle East and North Africa (MENA), where structural vulnerabilities—such as water scarcity, dependence on natural resources, and exposure to extreme heat—amplify the economic consequences of environmental shocks. The region is highly water-stressed, with sixteen of the twenty-five most water-stressed countries globally located in MENA (Carnegie Endowment, 2024), while coastal cities face growing threats from sea-level rise, projected to reach up to 0.6 meters by 2100 (World Bank, 2024). Additionally, the area is exposed to both recurrent droughts and flooding, and past climate disasters have led to permanent GDP losses of up to 1.1% (IMF, 2023).

As key financial intermediaries, banks play a central role in sustaining macroeconomic stability through their liquidity creation (LC) function, transforming illiquid assets into liquid liabilities that support consumption, investment, and risk-sharing. However, climate risk can undermine this function through multiple channels, including heightened credit and operational risk, asset devaluation, and shifting regulatory expectations. These pressures may influence not only lending behavior but also the broader spectrum of liquidity services provided by banks.

Research has predominantly focused on the relationship between climate risk and credit allocation, typically finding a negative association whereby banks reduce loan supply or shift their portfolios in response to physical and transition risks (Fatima and Ydriss, 2024; Aslan et al., 2022; Su et al., 2025). While such studies offer valuable insights into vulnerabilities within the credit channel, they often neglect the equally critical function of LC. As formalized by Berger and Bouwman (2009), LC encompasses not only loan issuance but also deposit mobilization and off-balance-sheet commitments such as guarantees and credit lines. This broader measure captures the systemic importance of banks in reallocating financial resources under uncertainty. Although one might expect heightened climate risk to trigger deposit outflows due to liquidity concerns or potential bank runs, emerging evidence suggests that banks can experience precautionary deposit inflows, especially in countries where deposit insurance is strong and households respond to macro-environmental uncertainty by saving more (Liu et al. (2025); Fernandes and Papadimitriou, 2025).

This study addresses this gap by investigating the impact of climate risk on bank liquidity generation, encompassing not only traditional lending but also deposit mobilization and off-balance-sheet activities. Furthermore, although the relationship between climate risk and financial stability has been acknowledged, limited attention has been paid to the nonlinear and heterogeneous effects across different risk regimes.

In the MENA region, the economic and financial effects of climate risks are not likely to increase in a straight, predictable way. For example, in Morocco, droughts cause only small GDP losses until rainfall drops below a certain point—then farm production and rural incomes fall sharply (World Bank, 2022). On the financial side, banks' ability to create liquidity can also change suddenly—such as when new regulations are introduced, when increased oil prices bring in large capital inflows, or when international donors send money after a climate disaster. These sudden shifts mean that climate change impacts and bank reactions are more likely to be uneven and unpredictable. A threshold-quantile method is better than simple linear models for studying this, because it shows not just whether climate risks matter, but how they affect different banks depending on the situation and where they stand on the LC scale.

Our empirical analysis is based on panel data covering 126 banks in 19 MENA countries over the period 2006–2022. The results reveal a threshold-dependent and heterogeneous effect: climate risk has a positive and significant impact on bank LC, but only beyond a certain level of risk exposure. This suggests that banks respond to heightened climate uncertainty by facilitating greater liquidity—likely driven by precautionary saving motives, deposit inflows, and flight-to-quality behavior. These findings contrast with those in the lending literature and highlight the importance of disaggregating financial channels when analyzing the climate–finance nexus.

This study contributes to three strands of literature. First, it extends climate finance research by focusing on LC, an under-explored but essential component of banking activity. Second, it adds to the literature on financial resilience in emerging and climate-exposed regions, using MENA as a case study. Third, it provides methodological innovation by employing threshold and distributional methods to uncover complex nonlinear effects.

The remainder of this paper is structured as follows. Section 2 reviews the related literature. Section 3 outlines the data and methodology. Section 4 presents the empirical results and interpretation. Section 5 concludes with key policy implications.

## 2. Literature Review

Most of the literature on climate risk and banking has concentrated on its impact on lending behavior. These studies commonly show that increasing climate vulnerability leads banks to contract their loan supply, reallocate credit away from environmentally exposed sectors, or raise the cost of capital in affected regions. For example, Su et al. (2025) demonstrate that physical climate events in Asia Pacific economies are associated with tighter credit terms and reduced loan volumes. Aslan et al. (2022) find that banks respond to long-term climate transition risk by reducing lending to carbon-intensive industries. Fatima and Ydriss (2024) explore how climate-related regulatory risk impacts loan growth and credit risk, particularly in developing economies. These findings collectively suggest that climate uncertainty undermines the credit function of banks through increased default risk, collateral impairment, and policy-induced portfolio adjustments.

### *2.1.* Liquidity Creation: A Broader Banking Function

While credit is a key function of banks, focusing solely on lending only provides a partial view of their role in the financial system. Banks also create liquidity by transforming illiquid assets into liquid liabilities and by offering off-balance-sheet commitments such as letters of credit, loan guarantees, and credit lines (Berger and Bouwman, 2009; Bryant, 1980; Diamond and Dybvig, 1983; Diamond and Rajan, 2001; Holmstrom and Tirole, 1997; Kashyap et al., 2002). This broader measure of LC is important for economic resilience, as it underpins both day-to-day financial transactions and long-term investment. This measure is widely used (Chaabouni et al., 2018; Davydov et al., 2018; Diaz and huang, 2017; Mdaghri, 2022; Elmahjoub et al., 2025)

However, the literature on climate risk has largely overlooked this broader intermediation channel. Few studies investigate how banks adjust their liquidity provision under environmental risk, even though LC may respond differently than credit supply—especially under uncertainty.

### *2.2.* Climate Risk and Financial Behavior: Theoretical Foundations

Contrary to the main findings in the lending literature, there are theoretical foundations for a positive relationship between climate risk and LC, particularly at higher risk levels. Two main channels explain this potential outcome.

First, the theory of precautionary savings suggests that households and firms increase their liquid asset holdings in times of uncertainty to buffer against future income shocks (Carroll, 1992). Climate risk, particularly when it becomes more salient or chronic, can trigger such behavior.

For example, using county-level heat stress data matched with household panel survey data, Liu et al. (2025) find that heat stress significantly increases household saving rates. Grounded in the precautionary savings motive, the authors show that heat stress raises household saving rates by exacerbating income and expenditure uncertainty. In the same vein, Fernandes and Papadimitriou (2025) investigate the impact of climate change exposure on firms' cash holdings. Using a large panel of mainly unlisted firms from 12-euro area countries Using a large panel of mainly unlisted firms from 12-euro area countries, the authors provide novel evidence which reveals that climate risk significantly affects the decisions of firms to hold more cash.

Second, the concept of flight to quality (Caballero and Krishnamurthy, 2008) describes how, under systemic stress, investors and depositors shift their resources toward safer financial institutions. In climate-exposed economies, regulated banks may be perceived as safer repositories for financial assets compared to non-bank intermediaries or informal saving channels. Ferriani et al. (2023) find that natural disasters in high-climate-risk emerging economies trigger a reallocation of international capital away from both affected and neighboring countries, and toward advanced economies viewed as climatically safer. This behavior reflects a re-pricing of climate risk and a search for “climatic safety,” a mechanism that can operate domestically through deposit inflows to perceived safe-haven banks.

While direct empirical evidence linking climate risk to bank LC remains scarce, studies on financial crises provide a strong theoretical foundation for expecting similar dynamics under climate stress. Climate shocks, like systemic financial crises, generate uncertainty about future incomes and asset values, prompting households and firms to increase liquid holdings and favor safer intermediaries. By adapting the precautionary savings and flight to quality frameworks to climate contexts, this study advances an under-explored area in banking research.

There is growing interest in sustainable finance and the MENA region presents distinctive features that make such analysis particularly relevant. Its economies rely heavily on bank-based finance and are exposed to both acute risks—such as severe droughts in Morocco and Tunisia (FAO, 2021), flash floods in Oman and Sudan (EM-DAT, 2023), and record-breaking heatwaves in Kuwait and the UAE (World Meteorological Organization, 2022)—and chronic threats like desertification and persistent temperature increases, which the World Bank projects to exceed 4°C by 2100 under high-emission scenarios (World Bank, 2021). Estimates suggest that climate-related water scarcity alone could cost the region up to 14% of GDP by 2050 (World Bank, 2017), while coastal flooding threatens major financial hubs such as Alexandria (IPCC, 2022).

Most research in this region examines energy transition, sovereign risk, or ESG performance, leaving the banking sector’s liquidity response to climate pressures largely unexamined. Our study addresses this gap by combining bank-level LC data with climate risk indicators and applying distributional methods that capture heterogeneous responses across different conditions.

The association between climate risk and bank LC may not be linear. Some studies on LC during systemic events suggest that banks respond differently depending on the severity of the shock. Cornett et al. (2011), for instance, find that during the global financial crisis, certain banks actually increased LC—especially those with stable liabilities or government support. This supports the idea that at lower levels of risk, banks may retrench, but beyond certain thresholds behavioral shifts (such as precautionary savings and flight to quality) dominate and lead to greater liquidity generation. These nonlinear effects justify our empirical choice to apply a dual threshold-quantile model, which can account for heterogeneity across risk levels and liquidity regimes.

### *2.3.* Hypotheses Development

Building on the theoretical foundations discussed above—precautionary savings and flight to quality—climate risk can influence banking behavior in a similar way. At low or moderate levels of risk, uncertainty may constrain lending and LC, as banks face potential asset deterioration, credit reallocation pressures, or income shocks to depositors. However, once climate risk surpasses a critical level, behavioral responses may dominate: households and firms increase deposits to buffer against income shocks (precautionary savings), and investors shift funds toward perceived safer banks (flight to quality). These mechanisms increase bank liabilities, deposits, and off-balance-sheet activity, thereby boosting LC.

This reasoning implies a nonlinear relationship: below a certain threshold of climate risk, the impact on LC may be weak or even negative; above that threshold, LC increases. Therefore, we formulate our first hypothesis:

***H1:*** Climate risk has a nonlinear effect on bank liquidity creation, with stronger positive impacts emerging only beyond a critical threshold of climate risk.

The behavioral response to climate risk is unlikely to be uniform across banks. Banks with different levels of LC may have different flexibility to adjust balance sheets or respond to increased deposits. Quantile-based approaches allow us to capture this heterogeneity. Accordingly, we propose our second hypothesis:

***H2:*** The relationship between climate risk and bank liquidity creation is heterogeneous across the distribution of liquidity creation.

## 3. Methodology and Data

### *3.1.* Data collection

We use the Bureau van Dijk BankFocus database and data from bank websites for bank-level data on bank financial statements and ratios for the period 2006–2022. Exclusionary criteria are applied to the initial sample of 160 banks, with non-commercial banks removed due to their distinct LC processes compared to commercial banks (Berger and Bouwman, 2017). After excluding banks with missing data, the final sample comprises 126 banks across 19 MENA countries. The additional country-level variables are gathered from World Bank databases.

Table 1 presents the number of banks and the average Climate Risk Index (CRI) for each country in our sample.

**Table 1:** Number of banks and mean Climate Risk Index (CRI) across countries

| *Country* | *Number of Banks* | *CRI* | *Country* | *Number of Banks* | *CRI* |
|---|---|---|---|---|---|
| ALGERIA | 7 | 46.16 | SYRIA | 2 | 40.85 |
| TUNISIA | 11 | 52.98 | PALESTINE | 1 | 46.74 |
| LIBYA | 4 | 46.87 | OMAN | 5 | 52.59 |
| MAURITANIA | 5 | 37.88 | LEBENON | 10 | 44.87 |
| MOROCCO | 4 | 49.89 | KUWAIT | 5 | 51.92 |
| TURKEY | 17 | 53.46 | JORDAN | 8 | 50.49 |
| UAE | 12 | 56.97 | IRAQ | 2 | 41.41 |
| QATAR | 4 | 56.88 | EGYPT | 15 | 45.93 |
| KSA | 8 | 51.58 | BAHRAIN | 5 | 51.86 |
| YEMEN | 1 | 37.58 | **TOTAL** | 126 | |

The table illustrates the countries, the number of banks and the average climate risk index (CRI) for each country in our sample.

***Source(s):*** *Table created by authors*

## 3.2. Variable definitions

### 3.2.1. The dependent variable: Liquidity creation

To measure bank LC, we adept the approach of Berger and Bouwman (2009), who classify balance sheet and off-balance sheet items into liquid, semi-liquid, and illiquid categories. The classification is based on the cost, ease, and time required for banks to meet their obligations to depositors and borrowers.

In the second step, each classified item is assigned a weight of 0.5, 0, or -0.5, reflecting its contribution to LC according to LC theory. Specifically, positive weights are assigned to illiquid assets (e.g., commercial loans) and liquid liabilities (e.g., demand deposits), as banks create liquidity by financing illiquid assets with liquid liabilities. Negative weights are assigned to liquid assets and illiquid liabilities, as these reduce LC when financing structures are reversed. Semi-liquid items receive a weight of zero.

In the third step, these weighted components are aggregated to calculate the LC value for each bank.

In this study, we compute LC for each bank-year observation using the calculation as in our empirical models (Equation 1). We adopt the broader "cat fat" measure of Berger and Bouwman (2009), which includes both on-balance sheet and off-balance sheet items (OBS), ensuring a comprehensive assessment of LC consistent with LC theory.

*LC = [½ × (illiquid assets + liquid liabilities + illiquid OBS) + 0 × (semiliquid assets + semi-liquid liabilities + semi-liquid OBS) – ½ × (liquid assets + illiquid liabilities + liquid OBS)]/Total assets (1)*

#### ***3.2.2. The independent variable: Climate risk***

The independent variable in our study is climate risk, represented by the Climate Risk Index (CRI), a composite measure developed by the German research organization Germanwatch. CRI captures the degree to which countries are exposed and vulnerable to extreme weather events by quantifying their direct impacts. Specifically, the index is constructed using four key components: the total number of fatalities (weighted at 1/6), fatalities per 100,000 people (1/3), total economic losses adjusted for purchasing power parity (1/6), and economic losses relative to GDP (1/3). These indicators collectively provide a balanced view of both the absolute and relative consequences of climate-related disasters.

Importantly, a lower CRI score implies a higher level of climate-related risk, as it indicates a higher rank in the severity of climate events. For instance, a country ranked 1st in terms of climate risk would have one of the lowest CRI scores, despite facing the highest actual risk. To improve interpretability within our regression framework—where higher values are typically associated with greater intensity—we multiply the CRI by –1. This linear transformation preserves the ordinal structure and distribution of the data while allowing for a more intuitive interpretation: higher (transformed) CRI values now correspond to higher levels of climate risk. This approach aligns with prior empirical studies that employ similar transformations for consistency in interpretation (Li and Wu, 2023; Huang et al., 2018).

#### ***2.2.3. Control variables***

We include a set of control variables at both the bank and country levels to account for factors that may influence LC.

*Bank-level controls:*

Deposit ratio (DEP): The proportion of total deposits to total assets captures the bank's funding structure. Banks with higher deposit funding are generally more stable and capable of creating liquidity (Díaz and Huang, 2017).

Bank size (SIZE): Measured as the natural logarithm of total bank assets, larger banks may benefit from economies of scale and risk diversification, enhancing LC (Berger et al., 2009).

Non-performing loans (NPLs): The ratio of non-performing loans to total loans proxies credit risk. Higher NPLs constrain lending capacity and reduce LC. Berger and Bouwman (2016) show that there is little research to date regarding this topic. They state that LC is positively related to liquidity risk, which may be positively associated with credit risk.

Profitability (ROA): Defined as the ratio of equity to total assets, more profitable banks can generate liquidity more effectively (Safiullah et al., 2022).

*Country-level controls:*

GDP growth (GDP): Annual GDP growth captures macroeconomic conditions. Strong economic growth supports credit demand and LC (Davydov et al., 2018).

Inflation (INFL): Measured by the growth rate of the Consumer Price Index. A high inflation can affect banks' balance sheet stability and LC (Elmahjoub et al., 2025).

Finally, global crisis (CRISIS) is included to investigate how bank LC responds during the crisis. A binary variable equal to one during the global financial crisis and COVID-19 pandemic periods (2007–2009, 2020–2022) and zero otherwise.

Table 2 summarizes the variables used in this study:

**Table 2:** Variable definitions

| **Variables** | **Definition** |
|---|---|
| LC | The "Cat fat" liquidity creation measure by Berger and Bouwman (2009) |
| **CRI** | The climate risk index that is calculated and published by the Germanwatch |
| **DEP** | The proportion of total deposits to total assets |
| **SIZE** | The logarithm of bank assets |
| **NPLs** | The ratio of NPLs to the total amount of loans |
| **ROA** | The ratio of equity to total assets |
| **GDP** | Annual GDP growth rate |
| **INFL** | Consumer Price Index (CRI) growth rate |
| **CRISES** | Binary variable equal to one in the period 2007–2009 and 2020-2022, zero otherwise |

***Source(s):*** *Table created by authors*

### *3.3.* Descriptive analysis and correlation matrix

#### *3.3.1. Descriptive analysis*

Table 3 provides the summary statistics of all the variables used in our study. The mean of total LC is 0.19, indicating that, on average, total LC represents 19% of gross total assets.

The average of CRI is -49.92, with the minimum of -59.96 and the maximum of -35.69, which shows that MENA's climate risk fluctuates significantly during 2006–2022.

**Table 3:** Summary statistics

| | *OBS* | *SD* | *Mean* | *Min* | *Max* |
|---|---|---|---|---|---|
| **LC** | 2142 | 0.27 | 0.19 | 0.01 | 1.32 |
| **CRI** | 2142 | 1.26 | -49.92 | -59.96 | -35.69 |
| **DEP** | 2142 | 0.81 | 0.57 | 0.00 | 0.92 |
| **SIZE** | 2142 | 2.04 | 10.25 | 4.88 | 16.21 |
| **NPLs** | 2142 | 0.06 | 0.10 | 0 | 0.67 |
| **ROA** | 2142 | 1.83 | 0.03 | -0.22 | 0.57 |
| **GDP** | 2142 | 0.10 | 0.10 | -0.52 | 0.32 |
| **INFL** | 2142 | 0.12 | 0.64 | -0.04 | 0.44 |

***Source(s):*** *Table created by authors*

#### *3.3.2. Correlation*

To evaluate the potential issue of multicollinearity among the explanatory variables we generate a correlation heatmap (Figure 1). The heatmap shows that the variables exhibit low pairwise correlations, suggesting that multicollinearity is not a significant concern in this analysis. This finding enhances the reliability of the regression results, ensuring that the estimated coefficients reflect the independent effects of each variable on emissions.

**Note**: In this heatmap, the diagonal values (correlation of a variable with itself) are shown in red. Positive correlations between different variables are displayed in beige (e.g., 0.413), while negative correlations are shown in blue. Grey represents a correlation close to zero. The intensity of the shading reflects the strength of the correlation, with darker tones indicating stronger relationships.

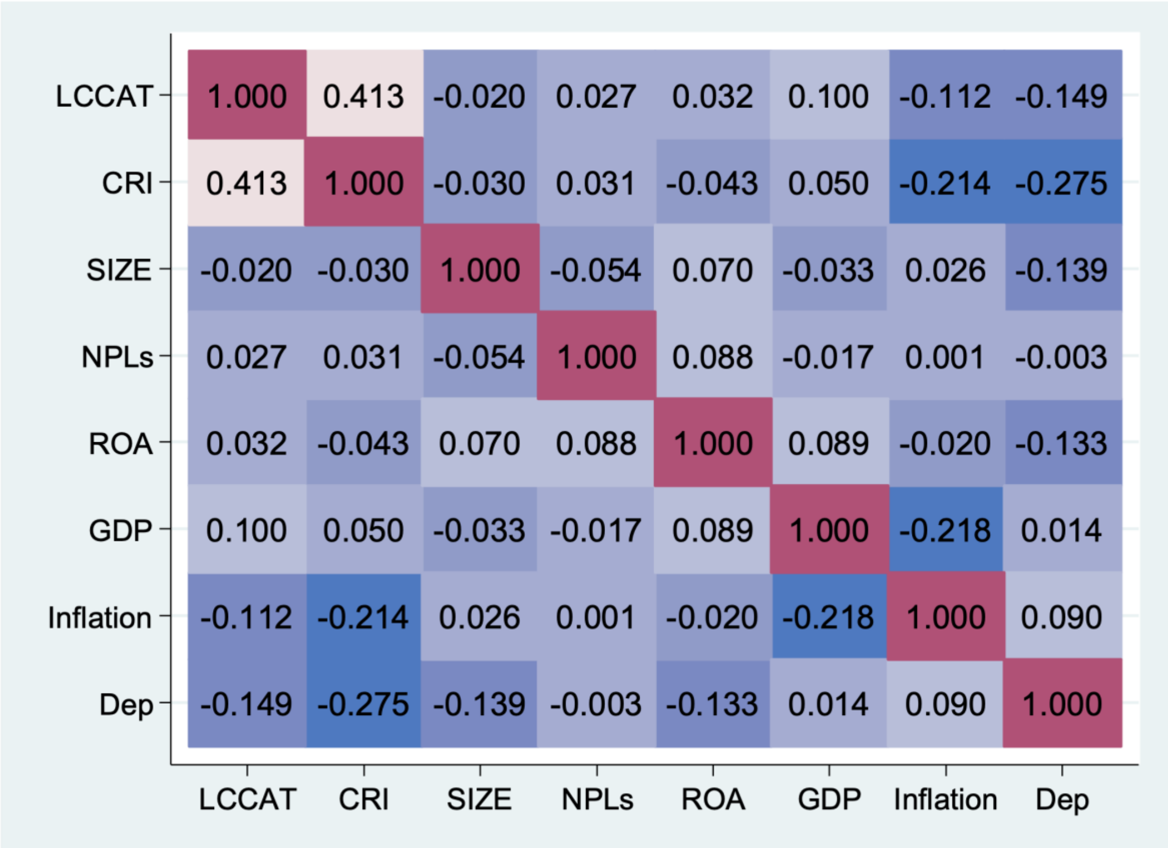


**Figure 1**: Correlation Heatmap

### *3.4.* Model specification

We employ a dual-method approach to examine the impact of climate risk on bank LC in the MENA region. First, we use a dynamic panel threshold regression model to identify potential critical climate risk levels at which the behavior of LC may change. Second, we apply quantile regression to explore heterogeneous effects of climate risk across different levels of LC.

To capture the potential nonlinear relationship between climate risk and LC, we implement the dynamic panel threshold model developed by Hansen (1999), specified as follows:

$$LC_{it} = \alpha_0 + LC_{it-1} + CRI_{it}\, I(CRI_{it} < \delta_1)\beta_1 + CRI_{it}\, I(\delta_1 \leq CRI_{it} < \delta_2)\beta_2 + \cdots + CRI_{it} I(\delta_n \geq CRI_{it})\beta_{n+1} + \alpha \sum Control_{it} + \mu_i + \Upsilon_t + \varepsilon_{it} \quad (2)$$

where $LC_{it}$ denotes LC for bank $i$ at time $t$, $CRI_{it}$ is the climate risk index, $I(\cdot)$ is the indicator function for threshold intervals, $\delta_j$ represent threshold values, $Control_{it}$ represents a set of control variables. *Year_FE* and *Bank_FE* denote year and bank fixed effects, respectively. Industry and year fixed effects ($\mu_i$ and $\gamma_i$) are used to control for unobserved factors and macroeconomic shocks.

To investigate the non-uniform effects of climate risk on LC, we employ a conditional quantile regression model defined as:

$$y_{it} = x'_{it} * \beta_{ө} + u_{өit}$$

$$Quantile_{ө}(y_{it} \mid x_{it}) \equiv \inf \{y : F_{it}(y|x)_{ө}\} = x'_{it} * \beta_{ө},$$

$$Quantile_{ө}(u_{өit} \mid x_{it}) = 0,$$

(3)

where Quantileө ($y_{it}|x_{it}$) gives the өth conditional quantile of $y_{it}$ on $x_{it}$. $\beta_{ө}$ is the unknown vector of parameters to be estimated for different values of in ө, (0< ө <1). $u_{өit}$ is the error term, a continuously differentiable cumulative density function of $F_{uө}$ (.|x) and a density function $f_{uө}$ (.|x). The value $F_{it}$(.|x) indicates the conditional distribution of the y conditional on x.

CRI may be endogenous due to omitted variables, measurement error, or reverse causality—where reduced LC could exacerbate climate vulnerability by limiting financing for adaptation. To address these issues, we employ the annual average precipitation as an instrumental variable for CRI. Precipitation influences CRI through its impact on extreme weather events but is exogenous to bank LC decisions, thus serving as a valid instrument to mitigate endogeneity bias.

# 4. Empirical results

## *4.1.* Baseline results

### *4.1.1. Threshold regression results*

Table 4 presents the estimates from the dynamic panel threshold model with endogenous regressors. The Supremum Wald (SupW) test provides strong statistical evidence supporting the presence of a threshold effect. The estimated threshold value of -46.38 on CRI divides the sample into two distinct regimes: regime 1, comprising banks in countries with CRI values less than or equal to this threshold (lower climate risk), and regime 2, including banks from countries where CRI exceeds this critical value (higher climate risk).

In regime 1, the relationship between climate risk and LC is statistically insignificant. This suggests that under relatively moderate climate risk conditions, banks do not significantly modify their LC behavior.

However, in regime 2—where climate risk intensifies beyond the estimated threshold—a positive and statistically significant relationship emerges between CRI and LC. In contrast to prior studies that document a negative impact of climate risk on bank lending (Faiella and Natoli, 2018; Ho and Wong, 2022; Ouazad and Kahn, 2022), this finding indicates that banks in high-risk environments may expand, rather than contract, LC.

This divergence can be explained by the broader scope of the LC concept adopted in this study. While most prior research focuses narrowly on credit supply, our LC measure (following Berger and Bouwman, 2009) captures a wider array of intermediation activities—including deposit-taking, on-balance sheet lending, and off-balance sheet commitments such as credit lines and loan guarantees. These off-balance sheet components are particularly important in the context of systemic uncertainty.

One key mechanism underpinning this result is the rise in precautionary savings behavior during periods of heightened climate uncertainty. Households and firms facing elevated environmental and economic risks tend to increase their holdings of liquid, safe financial assets to buffer against possible income shocks or disaster-related disruptions. This behavioral shift translates into greater deposit accumulation within the banking sector, thereby enhancing banks' capacity to create liquidity. Mody et al. (2012) support this mechanism and show that macroeconomic uncertainty leads to a significant increase in saving behavior across developed and emerging markets.

Another complementary explanation is the theory of flight to quality. As climate-related risks intensify, investors and depositors often reallocate their funds away from riskier financial instruments toward institutions perceived as safer and more stable. In the MENA region, where financial markets are relatively underdeveloped and informal finance is common, commercial banks—often supported by state backing and having regulatory oversight—become natural safe havens. This shift in capital flows strengthens the deposit base of banks and increases demand for liquid instruments and contingent lending, reinforcing their role as providers of systemic liquidity. This behavior is consistent with the theoretical framework of Caballero and Krishnamurthy (2008), and the empirical findings of Gatev and Strahan (2006), who show that banks benefit from increased deposit inflows during periods of market stress due to their perceived safety and liquidity provision capacity.

Berger and Bouwman (2017) show that in times of heightened financial risk, banks tend to increase LC, particularly through off-balance-sheet channels. This suggests that rising climate risk, far from only constraining banking activity, may lead to a compositional shift in how banks support liquidity in the economy—moving away from traditional lending toward contingent and diversified liquidity channels.

Taken together, these findings highlight the nonlinear and regime-dependent response of banking behavior to climate risk. The positive relationship between climate risk and LC above the threshold suggests that banks respond proactively under environmental stress, leveraging increased deposits and safe-haven status to expand liquidity provision.

**Table 4:** The impact of climate risk on liquidity creation: Estimation results of Panel Threshold Regression

| Dependent variable: LC | **Dynamic PT with endogenous regressors** |
|---|---|
| $LC_{t-1}$ | 0.254 (0.000)*** |
| **Panel A : Estimation of threshold effect** | |
| Threshold variable: CRI | The threshold value: **-46.38** |
| **Panel B : Impact of CRI on LC** | |
| Independent variable: CRI<br>**Below**<br>**Above** | <br>0.034 (0.126)<br>**0.047 (0.001)*** ** |
| **Panel C : Impact of control variables on LC** | |
| **SIZE** | 0.067*** (0.000) |
| **DEP** | 1.29*** (0.000) |
| **NPLs** | -0.41** (0.023) |
| **ROA** | 0.32** (0.017) |
| **GDP** | 1.21*** (0.000) |
| **INFL** | -0.61*** (0.000) |
| **CRISES** | -0.58** (0.021) |
| **Constant** | 0.419*** (0.000) |
| Time fixed effects<br>Bank fixed effects<br>SupW | YES<br>YES<br>**27.82*** ** |
| Note(s): *,** and *** indicate that the test results are significant at the 10% , 5% and 1% confidence levels respectively. The robust standard errors are reported. The annual average precipitation as the instrumental variable. | |

***Source(s):*** *Table created by authors*

### *4.1.2. Quantile regression results*

To further explore the heterogeneity in the relationship between climate risk and LC above the estimated threshold, we employ quantile regression on the sub-sample of banks operating in countries where CRI exceeds -46.38. While the previous threshold model confirms a statistically significant positive average effect of climate risk on LC in this regime, such a mean-based estimate may mask important distributional differences. Specifically, it is plausible that banks with varying initial levels of LC may respond differently to elevated climate risk—depending on their risk appetite, operational capacity, funding structure, or strategic priorities.

The results, presented in Table 5, reveal a clear non-uniform effect of climate risk across the conditional distribution of LC. The positive and significant relationship is concentrated in the intermediate quantiles of LC, notably between the 0.50 and 0.75 quantiles. This finding suggests that banks engaged in moderate levels of LC are the most responsive to rising climate risk. These banks may possess sufficient balance sheet flexibility and funding stability to scale up their liquidity support in response to depositor demand or precautionary funding needs, without being overly constrained by regulatory limits or excessive risk exposure.

From a behavioral and strategic perspective, mid-tier liquidity-creating banks are likely to experience the strongest marginal incentives to adapt during episodes of elevated climate uncertainty. They are neither too conservative to remain inert nor too leveraged to continue expanding. These institutions may respond to inflows of precautionary deposits—driven by household or firm behavior under environmental stress—or may actively reposition themselves as safe and responsive financial intermediaries in increasingly volatile environments.

In contrast, banks situated at the highest quantile (0.90) of LC exhibit a weaker and statistically insignificant response to additional climate risk. These banks may have already reached their LC capacity or may adopt more risk-averse strategies at high levels of liquidity exposure, choosing instead to focus on balance sheet consolidation, capital preservation, or diversification of exposures across regions and asset classes. Their relatively muted response is consistent with internal prudential limits and strategic diversification efforts that prioritize stability over expansion in high-risk scenarios.

The F-tests of coefficient equality across quantiles show significant differences in slope coefficients at the lower quantiles, suggesting that banks with initially low levels of LC respond heterogeneously to climate risk. These banks may be constrained by limited funding access, regulatory pressures, or weaker deposit bases, which dampen their ability to respond actively to climate risk shocks. On the other hand, the absence of significant coefficient variation among the higher quantiles implies that, despite differences in magnitude, banks with relatively high LC levels display a more stable and homogeneous behavioral pattern in the face of climate risk.

Overall, these findings reinforce the need to account for distributional heterogeneity in analyzing the climate–banking nexus. They demonstrate that the response of LC to climate risk is not uniform, but contingent on banks' pre-existing LC positions. By moving beyond average effects, the quantile regression framework uncovers important asymmetries that would otherwise remain obscured.

**Table 5**: The impact of climate risk on liquidity creation: Estimation results of Panel Quantile Regression

| | **0.25** | **0.50** | **0.75** | **0.90** |
|---|---|---|---|---|
| **CRI** | 0.004<br>(0.126) | 0.021***<br>(0.001) | 0.016***<br>(0.004) | 0.006**<br>(0.031) |
| **SIZE** | 0.67**<br>(0.034) | 0.60**<br>(0.012) | 0.71***<br>(0.004) | 0.66***<br>(0.001) |
| **DEP** | 1.54***<br>(0.000) | 1.05***<br>(0.000) | 1.84***<br>(0.000) | 1.33***<br>(0.000) |
| **ROA** | -0.60***<br>(0.000) | -0.38**<br>(0.34) | -0.64<br>(0.116) | 0.27**<br>(0.025) |
| **NPLs** | -1.85***<br>(0.000) | 0.92***<br>(0.000) | 0.75***<br>(0.000) | 0.59**<br>(0.022) |
| **GDP** | 1.15***<br>(0.000) | 1.44***<br>(0.001) | 1.38***<br>(0.005) | 1.42***<br>(0007) |
| **INFL** | -0.47***<br>(0.000) | -0.38**<br>(0.031) | 0.29<br>(0.165) | 0.16*<br>(0.071) |
| **CRISES** | -0.94***<br>(0.000) | -0.87***<br>(0.000) | -0.22**<br>(0.016) | -0.32*<br>(0.077) |
| **Pseudo $R^2$** | 0.211 | 0.201 | 0.304 | 0.296 |
| **Tests of the equality of slope estimates across various quantiles (F-tests)** | | 18.34 | 16.47 | 17.68 |
| **P- value** | | (0.000)*** | (0.157) | (0.106) |
| **Bank fixed effects: yes**<br>**Time fixed-effects: yes** | | | | |

Note(s): *,** and *** indicate that the test results are significant at the 10% , 5% and 1% confidence levels respectively. The robust standard errors are reported. The annual average precipitation as the instrumental variable.

***Source(s):*** *Table created by authors*

### *4.2.* Additional analysis: Quantile on quantile regression

To further validate the dual threshold-quantile methodology employed in analyzing the relationship between climate risk and LC, we implement a quantile-on-quantile regression (QQR). This approach offers complementary insights beyond those provided by threshold and quantile regressions by capturing heterogeneity and nonlinearity more granularly, potentially uncovering patterns that merit additional scrutiny.

The QQR results reveal a nuanced relationship between the Climate risk index and LC in the MENA region. Examining the full sample (Figure 2), we observe that low climate risk levels (quantiles between 0.05 and 0.10) exert no significant effect on LC across all LC quantiles. This suggests that banks perceive low-intensity climate shocks as background noise rather than systemic threats, consistent with the findings of Berger et al. (2023). In contrast, medium-to-high climate risk levels (quantiles above 0.15) are associated with significant positive effects on LC across all LC quantiles, indicating a systemic behavioral shift once climate risks exceed a critical threshold. This finding corroborates our main results regarding the existence of a threshold effect and aligns with Berger and Bouwman (2009), who document a positive association between LC and financial risk.

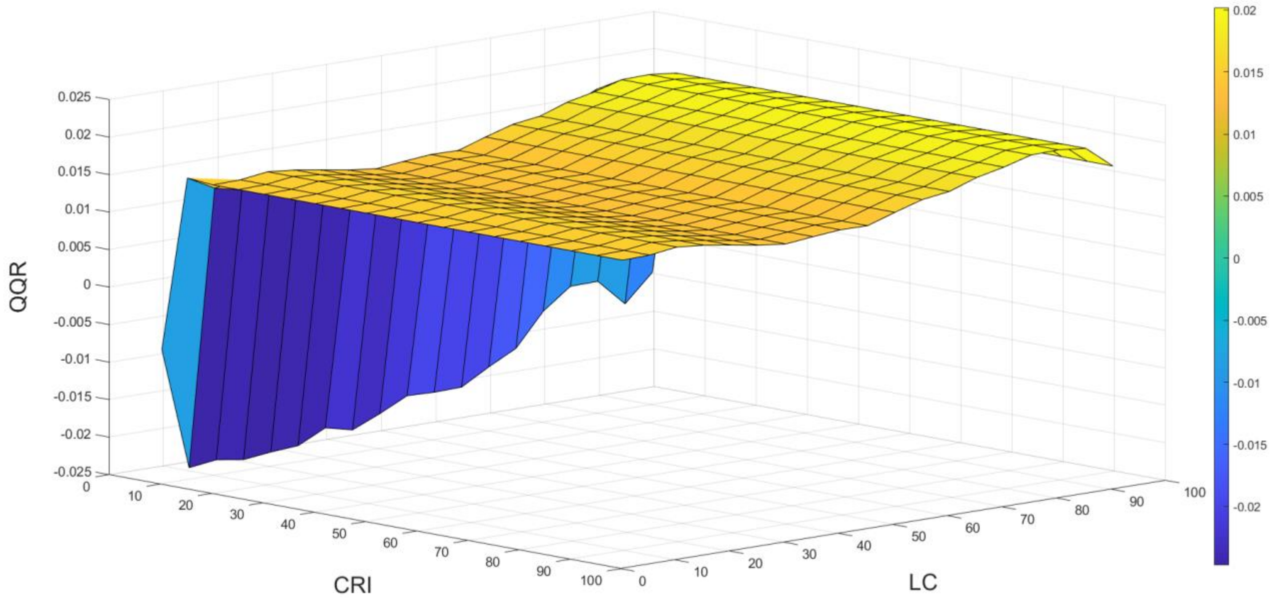


**Figure 2:** A 3D plot of the impact of CRI on LC (Whole sample)

When the analysis is restricted to observations above the threshold (CRI > -46.68; Figure 3), the positive impact of climate risk on LC persists but diminishes as climate risk intensifies. This pattern is consistent with Gennaioli et al. (2012), who argue that extreme disasters compel even aggressive banks to moderate their lending activities. Notably, banks at the lower quantiles of LC exhibit a muted response, which may reflect institutional safeguards in the MENA region, such as state guarantees, that mitigate panic and stabilize banking behavior (Delis et al., 2021).

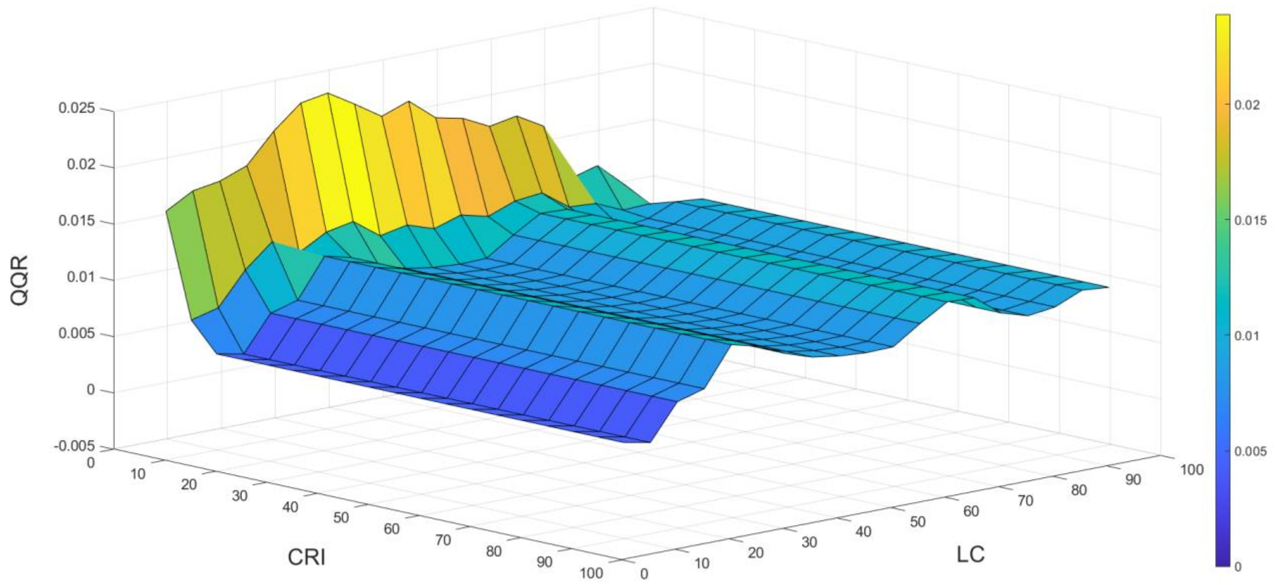


**Figure 3:** A 3D plot of the impact of CRI on LC (Above the threshold)

### *4.3.* Robustness check

#### *4.3.1. IV-GMM with Quadratic Term*

To assess the robustness of our results, we estimate a parametric IV-GMM specification that accounts for both endogeneity and nonlinearity. Specifically, we include a quadratic term of CRI to capture potential nonlinear effects. We use internal instruments, consisting of lagged values of the endogenous variables, and an external instrument, the annual average precipitation, which is correlated with the endogenous variable but is exogenous to the error term. We report standard diagnostics including first-stage F-statistics for instrument relevance and the Hansen J-test for over-identifying restrictions, as well as AR (1) and AR (2) tests in the panel setting. This approach provides a complementary robustness check to the dual-threshold quantile methodology, confirming that our main findings are not driven by endogeneity or the specific nonlinear functional form.

The results in Table 6 confirm both the presence of persistence and a nonlinear relationship between CRI and LC. The diagnostic tests confirm the reliability of the IV-GMM specification. The first-stage F-statistic (19.1) indicates strong instruments, while the Hansen J-test ($p = 0.326$) suggests that the over-identifying restrictions are valid. The AR (1) test detects first-order serial correlation, which is expected in differenced residuals, but the AR (2) test is insignificant ($p = 0.441$), confirming the validity of the lagged instruments.

**Table 6**: The impact of climate risk on liquidity creation: Estimation results of IV-GMM

| Dependent variable: LC | **Dynamic PT with endogenous regressors** |
|---|---|
| $LC_{t-1}$ | 0.394 (0.000)*** |
| **Panel A : Impact of CRI on LC** | |
| **CRI**<br>**Squared-CRI** | -0.04 (0.263)<br>**0.129 (0.000)***** |
| **Panel B : Impact of control variables on LC** | |
| **SIZE** | 0.154***<br>(0.001) |
| **DEP** | 1.694***<br>(0.000) |
| **NPLs** | -0.674**<br>(0.000) |
| **ROA** | 0.32**<br>(0.017) |
| **GDP** | 1.374***<br>(0.001) |
| **INFL** | -0.896***<br>(0.001) |
| **CRISES** | -0.786**<br>(0.014) |
| **Constant** | 0.266***<br>(0.000) |
| Time fixed effects<br>Bank fixed effects<br>First stage F<br>Hansen J<br>AR (1)<br>AR (2) | **YES**<br>**YES**<br>**19.1**<br>**2.14 (0.326)**<br>**-3.68 (0.000)*****<br>**0.92 (0.441)** |
| Note(s): *,** and *** indicate that the test results are significant at the 10% , 5% and 1% confidence levels respectively. The robust standard errors are reported. The annual average precipitation as the instrumental variable. | |

***Source(s):*** *Table created by authors*

### 4.3.2. *Alternative measure of LC*

To ensure our findings are not sensitive to the definition of LC, we employ an alternative measure of LC from Berger and Bouwman (2009) that excludes off-balance-sheet activities (e.g., loan commitments, guarantees) and captures LC solely through deposit-taking and lending activities.

We re-estimate our threshold regression model using this narrower LC measure.

**Table 7:** The impact of climate risk on LC under an alternative LC measure

| Dependent variable: LC | **Dynamic PT with endogenous regressors** |
|---|---|
| $LC_{t-1}$ | 0.163 (0.000)*** |
| **Panel A : Estimation of threshold effect** | |
| Threshold variable: CRI | The threshold value: **-42.17** |
| **Panel B : Impact of CRI on LC** | |
| Independent variable: CRI<br>**Below**<br>**Above** | <br>0.019 (0.263)<br>**0.022 (0.015)**** |
| **Panel C : Impact of control variables on LC** | |
| **SIZE** | 0.109***<br>(0.000) |
| **DEP** | 1.65***<br>(0.001) |
| **NPLs** | -0.35**<br>(0.017) |
| **ROA** | 0.38**<br>(0.026) |
| **GDP** | 1.08***<br>(0.001) |
| **INFL** | -0.46***<br>(0.000) |
| **CRISES** | -0.62**<br>(0.011) |
| **Constant** | 0.513***<br>(0.000) |
| Time fixed effects<br>Bank fixed effects<br>SupW | YES<br>YES<br>**25.13*** ** |

Note(s): *,** and *** indicate that the test results are significant at the 10% , 5% and 1% confidence levels respectively. The robust standard errors are reported. The annual average precipitation as the instrumental variable.

***Source(s):*** *Table created by authors*

Results presented in Table 7 remain broadly consistent with the baseline. Climate risk continues to exhibit a nonlinear relationship with LC, though the estimated threshold is slightly higher and the positive coefficient above the threshold is smaller in magnitude. While off-balance-sheet activities amplify the climate–liquidity channel, the core finding of a positive effect of high climate risk on LC is robust. This finding implies that the precautionary savings and flight-to-quality mechanisms remain active when considering only deposit-based LC.

Taken together, these results confirm the robustness of our main findings while clarifying that off-balance-sheet liquidity provision plays an amplifying role in the transmission of climate risk to LC.

## 5. Conclusion

This paper explores the complex and nonlinear relationship between climate risk and bank LC in the MENA region using a dual threshold-quantile methodology, further complemented by quantile-on-quantile analysis. By analyzing a panel of 126 banks across 19 countries from 2006 to 2022, our empirical results reveal that climate risk has a positive and heterogeneous effect on LC, but only when it exceeds a critical threshold.

Our results offer a number of contributions. First, we extend the literature on the effects of climate risk on financial intermediation by shifting the focus beyond traditional credit supply to encompass the broader concept of LC, a vital function for ensuring macroeconomic stability and resilience. Second, the adoption of a dual threshold-quantile approach enables us to uncover asymmetric responses among banks, offering deeper insight into how LC behavior varies not only across levels of climate risk but also across the distribution of banks' liquidity positions. This multi-dimensional heterogeneity reveals that mid-level liquidity-creating banks respond most strongly to climate risk, while highly active or passive banks adjust less aggressively.

From a theoretical standpoint, our findings resonate with the precautionary savings and flight-to-quality frameworks. In the face of heightened climate uncertainty, economic agents may seek safer financial havens, leading to deposit inflows and shifts in liquidity demand. Banks, in turn, respond to these dynamics by expanding LC, particularly in regimes where their operational flexibility allows them to absorb and redeploy such funds. However, this response is not limitless. When climate risk becomes excessively high or banks operate at the extremes of LC, risk aversion and capacity constraints can temper further liquidity expansion.

These nuanced results carry significant implications for policymakers, regulators, and financial institutions. First, central banks and supervisory authorities should recognize that banks' responses to climate risk are non-monotonic and regime-dependent. This calls for a more dynamic and targeted approach to climate stress testing, incorporating threshold-based triggers and distributional analysis rather than relying solely on average risk exposures. Stress testing models should account for the possibility that moderate climate shocks could induce liquidity expansion, while extreme shocks might constrain intermediation capacity or encourage excessive risk-taking in select institutions.

Second, financial regulators in the MENA region should integrate climate-sensitive indicators into the design of capital and liquidity requirements, ensuring that banks are adequately prepared to maintain liquidity support during climate-induced financial stress. Furthermore, given the prominence of off-balance sheet activities in LC, regulatory oversight must extend to contingent claims and credit lines that may be activated during environmental disruptions.

Third, for policymakers designing climate adaptation strategies, the results suggest that banks can serve as transmission channels for stabilizing liquidity—but only under specific conditions. Strengthening banks' resilience, improving climate-related disclosures, and encouraging green financial instruments can amplify the positive role banks can play in managing the liquidity consequences of climate volatility.

Lastly, our study offers a forward-looking perspective on the evolving role of banks under climate stress. As climate risk intensifies and global financial systems increasingly incorporate sustainability metrics, understanding the nonlinear and conditional nature of bank responses becomes essential. By shedding light on the heterogeneity of LC behavior across banks and regimes, this paper helps to pave the way for more informed, adaptive, and climate-responsive financial policies in the MENA region and beyond.

Future research could build on these findings by investigating the channels through which climate risk interacts with LC—such as changes in depositor behavior, funding market stress, or internal bank risk management—and by incorporating firm-level or regional climate exposure data to further refine the analysis.

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