Financial Intermediation of Insurance-Driven Liquidity: Evidence from Sovereign Climate Risk Pools

Abstract

This article studies the financial intermediation of insurance-driven liquidity shocks, a novel mechanism through which sovereign catastrophe risk pools affect financial sector stability in disaster-prone economies. Using data from the Caribbean Catastrophe Risk Insurance Facility (CCRIF) — the world's first sovereign climate risk pool — I exploit the exogenous shock from Tropical Cyclones Irma and Maria in 2017 to study the impact of insurance payouts on financial sector stability in small island developing states (SIDS) in the Eastern Caribbean. Difference-in-differences estimates show that banks in payout-receiving countries experienced a 122.8 percentage point increase in non-performing loans net of capital provisions relative to banks in non-recipient countries. Despite prudent use of liquidity to service existing non-performing loans, payout-receiving banks faced significant drawdowns in capital buffers and failed to achieve long-term solvency improvements. These results highlight the limits of insurance-based liquidity support in addressing deeper financial vulnerabilities following major climate shocks.

JEL Classification: D82, G22, Q54

Keywords: catastrophe insurance, SIDS, financial stability, climate risk pooling

1 Introduction

In his 1955 book, *The Theory of Economic Growth*, the father of Development Economics, Sir Arthur Lewis argued that prolonged periods of economic growth and stability could be disrupted by a number of factors, not least of which includes natural disasters. As a native of the Eastern Caribbean country of St. Lucia, the Nobel prize winning economist was acutely aware of the destabilizing impact of natural disasters on the financial and economic health of countries. Having served as an economic advisor to numerous Caribbean countries, were he alive today, it would, perhaps, please Sir Arthur that the world's first multi-country, sovereign risk pool for natural disasters was established by sixteen of these countries inclusive of his home country, St. Lucia.

An implicit aim of this kind of climate risk pooling is to support a country's financial stability following major disaster events. It is with this goal in mind, that small island developing states (SIDS) in the Caribbean, which are highly prone to natural disasters, established the Caribbean Catastrophe Risk Insurance Facility (CCRIF), a regional insurance company which provides parametric climate risk insurance to member countries. A subset of these countries are eight islands, in the Eastern Caribbean, which in 1983 combined their financial systems to form the Eastern Caribbean Currency Union (ECCU).

CCRIF not only has the distinction of being the world's first multi-country, sovereign risk pool but has also served as a model for the establishment of three other multi-country disaster risk sharing mechanisms among developing countries, namely, the Pacific Catastrophe Risk Insurance Company (PCRIC) which provides catastrophe risk insurance to 17 pacific islands countries, the South East Asia Disaster Risk Insurance Facility (SEADRIF) which caters to the catastrophe insurance needs of the 11 countries of the Association of Southeast Asian Nations (ASEAN) and the African Risk Capacity (ARC) Group which offers disaster risk insurance products to the 55 member states of the African Union. CCRIF, PCRIC, SEADRIF and ARC represent innovative risk sharing solutions that have supported developing countries financially during a decade of increased climate risk. Yet little is known about how effective these multi-country climate risk pools are at supporting economic recovery and financial stability in the aftermath of major climate events. The theoretical literature suggests that catastrophe risk pooling, while a useful financial tool, might be largely ineffective because of capacity constraints and non-diversification traps in reinsurance markets (Froot, 2008; Ibragimov et al., 2009). However, little empirical evidence exists on whether multi-country climate risk pooling overcomes these challenges. Since its establishment in 2007, CCRIF has, at the time of writing, made a total of 77 payouts, valued at US$385 million, following the advent of several major climate events which have affected Caribbean countries in recent times. A review of CCRIF payout data indicates that a significant portion (50%) of these payouts has been to the eight member countries of the ECCU. This article, therefore, exploits the ECCU setting to estimate the causal effect of insurance-based liquidity on financial sector stability in the aftermath of major climate shocks.

Existing work on catastrophe risk pooling has raised theoretical concerns about the effectiveness of catastrophe risk sharing mechanisms. A foundational perspective, as described by Froot (1997, 2001, 2008), emphasizes that traditional reinsurance markets are limited by capacity constraints and capital market imperfections. High premiums and limited availability of reinsurance after catastrophic events highlight inefficiencies in market pricing and suggest a structural constraint on risk-sharing. This view aligns with theoretical arguments by Ibragimov et al. (2009) on nondiversification traps, where insurers may avoid catastrophe risks due to the extreme tail risks associated with natural disasters, undermining optimal risk pooling and limiting market participation.

The Caribbean Catastrophe Risk Insurance Facility (CCRIF), and the other sovereign climate risk pools it has spawned, represents a practical application of these theoretical perspectives. By pooling catastrophe risks across multiple sovereigns and securing reinsurance coverage in advance, CCRIF directly addresses the non-diversification trap identified by Ibragimov et al. (2009) and mitigates the structural supply constraints described by Froot (2008). Rather than relying on fragmented post-disaster reinsurance markets prone to capital shortages and price spikes, CCRIF aggregates risks into a diversified portfolio that is more attractive to reinsurers. In addition, CCRIF's parametric structure — paying based on predefined disaster triggers rather than post-event claim assessments — avoids the costly delays and information frictions that typically weaken capital supply following major events. This rapid and predictable payout mechanism further strengthens CCRIF's ability to deliver timely liquidity when it is most needed. In doing so, CCRIF exemplifies how institutional innovation can partially overcome the traditional failures of catastrophe risk-sharing markets. Utilizing harmonized data on the 33 banks within the ECCU, this article empirically investigates the effect of this climate risk pooling on financial sector stability in the SIDS of the Eastern Caribbean. I answer one specific question. Does the insurance-based liquidity provided to countries by CCRIF following the advent of major climate events in the Eastern Caribbean improve the financial stability of ECCU banks?

To isolate exogenous exposure of ECCU banks to CCRIF insurance payouts, I exploit the shock to payouts following the passage of Tropical Cyclone Irma and Tropical Cyclone Maria in 2017. Both cyclones were significant climate events which resulted in large payouts and substantial financial impact across multiple Caribbean countries. As payouts are determined by random disaster events, this identification has plausible exogeneity. My causal identification strategy relies on variation in financial intermediation, by ECCU banks, of the insurance-based liquidity which flowed into the ECCU economy from CCRIF payouts following the cyclones.

While a rich literature examines the role of banks as liquidity providers under endogenous liquidity shocks, such as monetary policy tightening (Drechsler et al., 2017) or market-based funding dry-ups (Acharya and Mora, 2015; Carpinelli and Crosignani, 2021), much less is

known about how banks respond to exogenous, insurance-driven liquidity shocks following natural disasters. Studies such as Benmelech et al. (2017), Khwaja and Mian (2008), and Schnabl (2012) focus primarily on liquidity contractions within the banking system, with limited attention to external liquidity inflows sourced from sovereign insurance mechanisms. Moreover, while theoretical work underscores the systemic importance of insurance markets (IAIS, 2011), empirical evidence on the transmission of insurance payouts into domestic banking systems remains sparse. I addresses this gap by investigating the financial intermediation of insurance-based liquidity and providing new evidence on how banks in disaster-prone countries utilise externally-sourced liquidity in the aftermath of climate shocks.

What should we expect to see when additional liquidity from an exogenous shock flows into the banking system? Recent work by Altavilla et al. (2025) in the context of central bank liquidity provided to European Union (EU) banks through quantitative easing indicate that banks tend to expand credit, particularly if they were previously liquidity constrained. A more general model of how banks respond to exogenous liquidity inflows, irrespective of the source (central bank or otherwise) implies that banks maximise a utility (profit) function not only over returns but also over regulatory compliance, risk mitigation, and financial resilience. This model serves the ECCU setting well as it introduces additional uses of liquidity which would apply in the aftermath of major climate events. While existing models of financial intermediation under liquidity shocks focus on monetary or depositor-driven liquidity sources (e.g., Altavilla et al., 2025; Acharya and Rajan, 2024), this article introduces a novel setting where liquidity enters the financial system exogenously through sovereign insurance payouts. This form of insurance-based liquidity is mediated by government fiscal responses and borrower cash flows, creating distinct dynamics in bank balance sheets, credit supply, and solvency restoration compared to traditional monetary interventions. In this setting, in addition to expanding credit, banks may use the additional liquidity to provision for losses, clean up balance sheets, or restructure loans. Banks may also utilize the inflow as capital buffer to address longer-term solvency problems so as to enhance financial stability.

This article examines the distinct dynamics of the financial intermediation of insurance-based liquidity, using the 2017 CCRIF payouts triggered by Tropical Cyclones Irma and Maria as a quasi-experimental setting. Employing a difference-in-differences design, I compare the post-disaster financial stability outcomes of banks in payout-receiving ECCU countries to banks in non-recipient countries, testing the parallel trends assumption using dynamic event studies.

The evidence reveals several key insights. First, although CCRIF payouts provided immediate liquidity relief that banks prudently applied toward servicing non-performing loans (NPLs) rather than expanding new credit, this strategy came at the cost of deteriorating capital adequacy. Non-performing loans net of provisions increased by 122.8 percentage points among treatment banks, suggesting that payout inflows were insufficient to fully offset rising credit risks. Second, dynamic event studies show that liquidity indicators improved sharply in

the short term but declined thereafter, whereas solvency indicators exhibited no statistically significant long-term improvements. Models with and without lagged dependent variables consistently indicate that the liquidity effects were transitory and did not structurally improve bank balance sheets, supporting a short-term liquidity hypothesis over a long-term solvency improvement hypothesis. Third, credit issuance declined significantly post-payout, confirming that banks prioritized stabilizing legacy loan books over risky lending expansion. Even selective sectoral lending increases were modest compared to the broad credit contraction observed. Banks largely rationed new credit issuance for at least three years post-event. Additionally, profitability and operational efficiency deteriorated: interest margins steadily declined, non-interest expenses rose persistently, and the deterioration was most severe among banks with weaker pre-disaster balance sheets. These patterns align with the "bad luck" hypothesis of Berger and DeYoung (1997), suggesting that exogenous shocks imposed long-term operational strains on financial institutions through elevated NPL servicing costs. Furthermore, macroeconomic comparisons between treatment and control countries show that CCRIF payouts cushioned the broader economic contraction, but the magnitude of payouts was too small relative to the scale of damages to fundamentally restore financial sector resilience.

Overall, these results highlight the limitations of climate risk pools like CCRIF: while highly effective in providing short-term liquidity and preventing immediate systemic collapse, they fall short of addressing deeper solvency and profitability challenges in the banking sector after severe disasters. Climate risk pooling therefore constitutes a necessary but insufficient mechanism for safeguarding long-term financial stability in Small Island Developing States.

This article contributes to several strands of literature. First, it extends research on the financial intermediation and pricing of climate risk, a literature which has focused predominantly on catastrophe bond and reinsurance markets (von Dahlen and von Peter, 2012; Gotze and Gurtler, 2020; Rousova et al., 2021; Basten and Karthasheva, 2024; Tomunen, 2025). To the best of my knowledge, this is the first empirical study of sovereign climate risk pools — such as CCRIF — and their impact on financial sector stability. Second, this article is among the first to examine the financial intermediation of climate risk in Small Island Developing States (SIDS), where climate vulnerability is particularly acute. While some grey literature describes the operations of multi-country risk pools (Cummings and Mahul, 2008; Broberg and Hovani, 2019), no empirical studies have evaluated their effectiveness in supporting the financial stability of beneficiary countries.

Third, this article deepens understanding of how exogenous liquidity injections — in this case via catastrophe insurance payouts rather than central bank interventions — affect bank balance sheets and financial resilience after major disasters. While existing studies of liquidity shocks primarily focus on monetary policy tools such as quantitative easing (Acharya and Rajan, 2024; Altavilla et al., 2025), I show how insurance-driven liquidity relief produces distinct short-term and long-term dynamics in fragile banking systems. This line of inquiry extends

central bank liquidity lessons to insurance-based liquidity, which is more external and ad-hoc rather than monetary policy-driven. Finally, this article contributes to the broader literature on catastrophe and climate risk pooling (Froot, 2008; Ibragimov et al., 2009; Garmaise and Moskowitz, 2009; Wagner, 2022; von Peter et al., 2024) and on the financial sector impacts of natural disasters, particularly within the context of vulnerable developing economies.

The financial sector impacts of natural disasters present distinct dynamics between developed North American economies, where much of the literature is focused, and Small Island Developing States (SIDS) within the Eastern Caribbean Currency Union (ECCU). Studies focused on North America highlight how large, diversified financial institutions adapt to disaster-induced risks through capital reallocation, securitization, and risk transfer, leveraging complex financial systems. Conversely, research on the ECCU underscores vulnerabilities stemming from its concentrated financial structures, reliance on deposits, and limited access to broader financial markets.

In North America, banks leverage their geographical and operational reach to stabilize credit markets in disaster-affected areas. Cortes and Strahan (2017) show that multi-market banks respond to increased credit demand post-disaster by reallocating funds to impacted regions, often at the expense of credit availability in unaffected but interconnected areas. This capital reallocation demonstrates how integrated banking systems can act as a stabilizing force by supporting local credit needs. Blickle et al. (2022) argue that U.S. banks can benefit from disaster-induced loan demand, underscoring their resilience and adaptability. Banks often see a surge in loan applications for rebuilding, translating into increased profits. Meanwhile, Schuwer et al. (2019) highlight that independent banks in disaster-prone areas maintain higher capital buffers to hedge against disaster-related income shocks, showing defensive strategies.

In contrast, the ECCU's financial sector faces unique challenges rooted in its narrower economic structure and heightened exposure to disasters. Brei et al. (2019) document that natural disasters lead to funding shocks as deposit withdrawals spike post-disaster, prompting ECCU banks to draw down on liquid assets and scale back lending to meet demand. Unlike North American banks, ECCU banks lack diversified funding sources and limited access to capital markets, making them highly vulnerable to liquidity strains without the benefit of reallocation mechanisms seen in larger economies. I advance this work by studying whether or not the climate risk pooling, pioneered by CCRIF, alleviates these shocks to ECCU financial sector stability.

The remainder of the paper is organized as follows. Sections 2 presents the institutional background for both CCRIF and the ECCU and also discusses the financial intermediation of CCRIF insurance payouts by ECCU financial institutions. Section 3 describes the data and outlines the empirical strategy. The article advances in Section 4 where results are presented and discussed. The article ends with concluding discussions in Section 5.

2 Institutional Background

2.1 Background to CCRIF

The Caribbean Catastrophe Risk Insurance Facility (CCRIF), now operating as CCRIF SPC, was established in 2007 in response to the severe financial strain that Caribbean countries face after natural disasters. The concept for CCRIF was prompted by the devastating impact of Hurricane Ivan in 2004, which caused billions of dollars in damages across the region, especially in Grenada and the Cayman Islands, where losses equaled nearly 200% of their GDP.

CCRIF uses a parametric insurance model, meaning payouts are triggered based on the occurrence of a pre-defined event (e.g., a hurricane or earthquake) and the modelled loss rather than the actual losses incurred on the ground. This enables quicker payouts. Policies cover risks such as tropical cyclones, earthquakes, and excess rainfall. Each country has unique coverage limits, deductibles, and premium structures, allowing for customisation according to specific risk profiles. Figure A3 in online Appendix C1 shows the total payout values to date for polices which cover tropical cyclones and excess rainfall, climate events which have become more frequent and to which the SIDs within the ECCU are most prone.

CCRIF aggregates disaster risks across its 17 members, achieving regional risk diversification. This pooling reduces the overall risk profile and makes it more attractive and cost-effective to reinsurers. CCRIF retains a portion of the risk within its own capital reserves (approximately $35.65 million for 2017/18). The remaining risk is transferred to the reinsurance market. For the 2017/18 policy year, CCRIF had reinsurance coverage up to a 1-in-1,000-year loss event ($205 million). CCRIF partners with globally recognised reinsurance brokers and firms to secure coverage. Willis Re serves as the reinsurance broker, ensuring competitive rates and high-quality coverage.

The facility operates as a Segregated Portfolio Company (SPC), enabling the complete segregation of risk and facilitating the management of distinct insurance portfolios. This structure allows CCRIF to expand its range of products, including the planned Loan Portfolio Cover (LPC) to protect financial institutions. Member governments pay annual premiums, and in return, receive immediate payouts when disaster thresholds are met, thereby addressing short-term cash flow problems that governments encounter after a disaster. The fund is also capitalized through grants from multilateral bodies such as the World Bank and the European Union.

2.2 Background to the ECCU

The Eastern Caribbean Currency Union (ECCU) is one of the oldest and most stable currency unions in the world. It was formally established in 1983 with the creation of the Eastern

Caribbean Central Bank (ECCB), which replaced the Eastern Caribbean Currency Authority. The ECCB is responsible for managing the Eastern Caribbean dollar (EC$), a currency that has been pegged to the US dollar since 1976 at a rate of 2.7 EC$ to 1 US$. This peg has been critical to maintaining price stability and low inflation across ECCU member states.

The ECCU comprises eight members of the Organization of Eastern Caribbean States (OECS), namely Antigua and Barbuda, Dominica, Grenada, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Anguilla, and Montserrat. These countries share a common currency, monetary policy, and a regional central bank, but maintain individual fiscal policies. The economies of these nations are small, open, and highly dependent on tourism, agriculture, and, to a lesser extent, financial services.

One of the ECCU's key challenges is its vulnerability to external shocks, particularly natural disasters. The region's geographic location makes it highly susceptible to hurricanes, which can cause significant economic disruptions. This economic fragility is compounded by the region's reliance on a limited number of sectors, notably tourism, which can be severely affected by such disasters. The 33 ECCU financial institutions which are regulated by the ECCB have experienced an increase in disaster events since 2008. Figure A1 in online Appendix C1 shows the number of financial institutions for each country within the ECCU while Figure A2, also in the online Appendix C1, shows the increase in disaster events.

2.3 Transmission Mechanism of CCRIF Payouts in the ECCU

The Eastern Caribbean Currency Union (ECCU), characterized by high financial integration and a heavily financialized economy, benefits from CCRIF payouts primarily through an indirect transmission mechanism rather than direct injections to financial institutions. This section examines the economic pathway through which CCRIF payouts impact financial stability in the ECCU, highlighting the roles of government spending, financial intermediation, and economic stabilization. A theoretical model is presented in online Appendix B.

CCRIF payouts are structured as parametric insurance, providing rapid liquidity to governments. These funds are crucial for SIDS, where immediate access to capital is limited, especially after disasters that disrupt revenue and increase the fiscal burden on the state. Governments use CCRIF payouts primarily for emergency relief, rebuilding infrastructure, and restoring essential services, thereby kickstarting the recovery process. This immediate response mitigates the risk of prolonged economic downturns and reduces the likelihood of cascading defaults and economic stress, which could otherwise directly impact financial institutions through higher non-performing loans (NPLs).

In the ECCU, financial institutions indirectly benefit from CCRIF payouts through the process of financial intermediation, where funds received by the government enter the broader economy and circulate through the banking sector. As governments deploy CCRIF funds for

capital expenditure on infrastructure and disaster recovery, they create demand for goods, services, and labor, which stimulates economic activity. This increase in economic activity generates new income for households and businesses, ultimately improving their ability to service debts. In a financialized economy like the ECCU, with strong interconnections between the public sector, households, and financial institutions, such liquidity injections have a multiplier effect. The funds support loan repayment and boost demand for new credit, which positively impacts banks' balance sheets and stabilizes regulatory capital-to-risk-weighted assets ratios. Online Appendix C3 presents difference-in-differences results which demonstrate that CCRIF payouts had a demonstrably positive impact on the capital expenditure of ECCU governments in the aftermath of the 2017 cyclones.

The ability of households and businesses to meet financial obligations directly influences the non-performing loan ratio, a key determinant of financial stability. As CCRIF funds bolster economic activity, the overall financial health of borrowers improves, reducing NPLs and positively impacting financial institutions' balance sheets. Additionally, as the economy stabilizes, financial institutions may experience increased demand for credit, providing further opportunities to strengthen their capital base through profitable lending.

The ECCU's high degree of financial integration amplifies the transmission mechanism of CCRIF payouts. The region's financial institutions are interconnected through cross-border banking, shared monetary policy, and integrated capital markets. As such, liquidity injected into one part of the economy—especially following a systemic shock like a natural disaster—flows more readily throughout the entire financial system. This interconnectedness means that government spending following CCRIF payouts ultimately supports financial institutions by stabilizing the economic environment in which they operate. Thus, the transmission mechanism is enhanced by the ECCU's financial integration, ensuring that even indirect financial benefits from CCRIF payouts reach financial institutions and contribute to broader financial stability.

This article introduces and empirically examines this novel mechanism of financial intermediation: insurance-driven liquidity following sovereign catastrophe risk pooling. Unlike traditional liquidity shocks originating from monetary policy interventions or deposit flows, insurance payouts under sovereign risk pools inject liquidity into the economy indirectly through government fiscal responses and borrower cash flows. I show that while this exogenous liquidity boost initially strengthens bank liquidity positions, it does not restore long-term solvency. Instead, banks use the inflow defensively to stabilise existing non-performing loans, at the cost of capital drawdown, profitability erosion, and persistent financial vulnerability. These findings deepen our understanding of how the source, structure, and transmission channel of liquidity shocks critically shape financial stability outcomes in disaster-exposed economies.

3 Data and Empirical Strategy

3.1 Data and Summary Statistics

I use data on the 33 financial institutions within the ECCU provided by the ECCB monetary and financial statistics database. I collect data on several financial stability measures relating to capital adequacy and liquidity. These are described in Table 1. I construct a balanced panel of the 33 financial institutions for 2008-2023 and obtain 528 financial institution-year observations.

Insert Table 1 here

The summary statistics, presented in Table 2, show that on average ECCU financial institutions exhibit strong capital adequacy ratios in terms of both total regulatory capital and Tier 1 capital, indicating a relatively stable and well-capitalized financial sector. ECCU financial institutions have regulatory capital that is approximately 19.54% of their risk-weighted assets. This level is generally considered healthy, as it is above the international minimum regulatory requirement set by the Basel III framework (which is typically 8% or higher depending on jurisdiction). The core capital (Tier 1 capital) of ECCU financial institutions, which includes shareholders' equity and retained earnings, is around 17.13% of their risk-weighted assets. This figure also reflects a strong capital position, as Tier 1 capital is the most crucial buffer against financial instability.

The average value of Non-Performing Loans (NPLs) net of capital provisions in the ECCU, reported as 37.44 with a standard deviation of 167.63, suggests significant variation in uncovered credit risk across banks and countries. The measure captures the extent to which banking sector exposures are covered by capital buffers, with higher values indicating weaker financial stability. A positive mean implies that, on average, banks hold fewer capital provisions than the total value of their NPLs, indicating potential vulnerabilities in the banking sector's shock absorption capacity. However, the large standard deviation — over four times the mean — signals the presence of extreme values or substantial heterogeneity in financial resilience among ECCU banks. Some banks may be well-capitalised, while others face elevated risk of under-provisioning.

Figure A6 in online Appendix C2 displays the distribution of NPLs net of capital provisions across the eight ECCU member states. Banks in St. Lucia, Dominica, and Anguilla exhibit the highest levels of NPLs net of provisions, suggesting relatively greater exposure to uncovered credit risk. In contrast, banks in Antigua and Barbuda displays a negative value, indicating that capital provisions exceed reported NPLs, potentially reflecting a more conservative provisioning approach or improved asset quality. Banks in smaller economies such as Montserrat report comparatively low net NPL levels. Overall, the chart highlights substantial cross-country variation in financial stability.

In terms of liquidity, on average, ECCU banks display strong liquidity levels, with a substantial portion of their assets in liquid form and a strong ability to cover short-term liabilities. On average, ECCU financial institutions hold 40.95% of their total assets in liquid form and liquid assets cover nearly half of short-term liabilities (45.90%).

Insert Table 2 here

Data on CCRIF payouts are obtained from the list of payouts posted to CCRIF's website. For each country in the ECCU which receives a payout over the sample period, I collect the payout amount, the payout frequency and the type of policy from which the payout is being made. I calculate the annual payout rate, as the percentage of the annual payout relative to the average annual payout over the period, and deploy this measure as my main independent variable. I also obtain data on and control for the number and types of disaster events for which payouts are made. As indicated in Table 2, the average payout is valued at $16.5 million USD, the average payout rate is 100% and the average number of payouts over the sample period is 4. The average number of disaster events for which CCRIF makes a payout is 2.

I also collect data for a set of control variables obtained from the monetary survey maintained in the ECCB monetary and financial statistics database. Catastrophic events can affect a country's financial stability through external channels. For instance, they can lead to sudden outflows of capital, impact foreign investor confidence, and necessitate borrowing from abroad to finance recovery efforts. I, therefore, include net foreign assets as a control variable to isolate the impact of catastrophe insurance on financial stability by accounting for the external balance sheet effects and potential external funding needs in the aftermath of catastrophes. This allows for a more accurate assessment of how well catastrophe insurance contributes to financial stability. I also collect data for claims on private sector to control for credit risk exposure of the financial system and broad money liabilities (M2) to control for the liquidity position of the financial sector.

For each country in the dataset, I obtain a range of macro level control variables which control for measures of the general economic environment which are macroeconomic determinants of financial stability. These include the end of period inflation rate as measured by the consumer price index, the real effective exchange rate, short term interest rates, long term interest rates and official development assistance in the form of grants which are expected to increase following natural disasters. Table 1 lists and defines all the variables utilized in the empirical analysis. I provide additional details on data sources in online Appendix A.

3.2 Empirical Strategy

To estimate the causal effect of CCRIF payouts on financial stability in SIDS in the Eastern Caribbean, I rely on the large exogenous shock to payouts caused by Tropical Cyclone Irma

and Tropical Cyclone Maria in 2017. Figure A4 and Figure A5 in online Appendix C1 confirm the increase in both the number and value of payouts in 2017. From this event, I obtain plausible exogenous variation in CCRIF payouts for a sample of treated financial institutions relative to a comparable set of control financial institutions. The treatment group is comprised of financial institutions in ECCU countries which receive a CCRIF payout while the control group is comprised of financial institutions in countries which do not receive a payout. I compare both sets of financial institutions before and after the shock in a difference-in-differences framework. I focus on NPLs net of capital provisions as a headline indicator of financial stability and utilize the general DiD model specified as follows:

$$\begin{aligned} Y_{ijt} = \beta_0 + \beta_1(\text{Payout Treat}_{ij} \times \text{Post}_t) \\ + \gamma X_{ijt} + \alpha_i + \lambda_t + \mu_c + \epsilon_{it} \end{aligned} \tag{1}$$

Where Y_{ijt} is NPLs net of capital provision for financial institution i, in country j, in year t. Payout $\text{Treat}_{ij} \times \text{Post}_t$ is the interaction term capturing the differential impact of payouts after 2017. X_{ijt} represents the control variables. The unit of observation is the financial institution-year. To control for unobserved characteristics at the financial institution level, country level, currency union level and regulatory supervision level, I include saturated financial institutions-country-ECCU-ECCB supervision fixed effects. I also include year fixed effects and disaster fixed effects. Standard errors are double-clustered by financial institution-year to account for both cross-institution correlations within years and serial correlations within institutions over time.

To study the dynamics of financial stability, I estimate the following dynamic event study models with and without lagged dependent variables included as a regressor:

$$Y_{ijt} = \sum_{\tau=-9}^{5} \beta_\tau D_{i,\tau} + \gamma X_{ijt} + \alpha_i + \lambda_t + \mu_c + \epsilon_{it} \tag{2}$$

$$Y_{ijt} = Y_{ijt-1} + \sum_{\tau=-9}^{5} \beta_\tau D_{i,\tau} + \gamma X_{ijt} + \alpha_i + \lambda_t + \mu_c + \epsilon_{it} \tag{3}$$

Y_{ijt} represents the unlagged dependent variables while Y_{ijt-1} represents the lagged dependent variables. The vector $D_{i,\tau}$ captures dummies for each year around the shock, and ranges from nine years before and five years after. The controls and fixed effects are as previously defined.

4 Results

4.1. CCRIF Payouts and NPLs Net of Capital Provisions

The first line of defense that banks have in the event of the financial disruption caused by catastrophic events is the loan loss provisions they are required to set aside in the event of loan defaults. The impact of the additional liquidity which flows into the financial system from CCRIF payouts on these capital buffers depends on how this liquidity is utilized and on how badly affected borrowers are by the disaster which triggers the payout. To examine what transpired in the case of ECCU banks following the passage of Tropical Cyclones Irma and Maria in 2017, I begin by using equation (1) to estimate the differential impact of CCRIF payouts on NPLs net of capital provisions between banks in countries which received payouts and those in countries which did not.

In the aftermath of the 2017 cyclones, ECCU banks in payout-receiving countries seem to have had less capital buffers to handle loan defaults as they experienced a greater increase in NPLs net of capital provisions compared to banks in countries which did not receive a payout. Table 3, which presents the estimates of equation (1), suggests that the rise in NPLs outpaced the increase in the additional liquidity that banks would have presumably used to shore up provisioning for NPLs. In the first column which only includes year and financial institution fixed effects, a coefficient of 107.7 implies that, after receiving CCRIF payouts, nonperforming loans net of capital provisions was approximately 107.7 percentage points higher in the treatment group when compared to the control group. In column 2, which presents estimates of the more restrictive model where controls and saturated fixed effects are included, the difference is even more significant at 122.8 percentage points.

Insert Table 3 here

I present the parallel trend plots which illustrates these results in Figure 1. Pre-2017, the treatment group shows a slightly higher level of nonperforming loans relative to capital compared to the control group, but the trends are similar overall. This pre-2017 parallelism adds credibility to the assumption that the two groups would have continued on similar trajectories without the shock. Post-2017, NPLs relative to capital in the treatment group remain elevated above that of the control group. This pattern aligns with the large and significant coefficients observed in the regression results, indicating that banks in payout-receiving countries suffered greater loan defaults, which significantly worsened their financial stability.

Insert Figure 1 here

To zoom in more closely on how the effect of CCRIF payouts evolved among banks in the treatment group, I conduct event studies, using equation (2) and (3), to capture both short-term and longer-term effects. The event study results which do not include the lagged dependent

variable as a regressor are graphically represented in Figure 2 while the results which include the lagged dependent variable as a regressor are presented in Figure A22 of online Appendix D.

Insert Figure 2 here

As shown in Figure 2, there is a sharp increase in NPLs net of capital provisions in the years leading up to the disaster event (years -9 to -4). This suggests that banks were accumulating bad loans or provisioning inadequately before the payouts, leading to capital adequacy deterioration. Around year -3, the trend reverses, and nonperforming loans begin to decrease as financial institutions might have taken steps to address these challenges. As already shown in the parallel trend plots in Figure 1, the year 0 result shows a substantial decline in the ratio of NPLs net of provisions to capital, suggesting an immediate positive impact of the payout. Post-payout, the level of NPLs net of provisions to capital remains low, with some fluctuations, but generally remains lower than the pre-payout period. Figure A20 in the online appendix shows a similar pattern.

When looked at in isolation, the event study results would seem to suggest that the payouts allowed banks in the treatment group to effectively manage loan defaults through greater capital provisioning, but as shown in Figure 1, which compares the treatment group to the control group, banks in countries which received payouts appeared to have, on average, feared worse off in-terms of the impact of loan defaults on their financial stability as the level of NPLs net of capital provisions over the entire post-payout period is higher for banks in payout-receiving countries when compared to that of banks in countries which did not receive a payout.

Why did the banks in countries which received payouts fare worse off than the banks in countries which did not? There are three possible reasons. First, the short-term liquidity provided by CCRIF payouts might have been insufficient to improve long-term solvency and as such may have primarily addressed liquidity issues without resolving deeper solvency problems. As a result, banks might have underestimated the long-term damage to borrowers and failed to scale up capital provisions adequately, focusing instead on short-term liquidity as opposed to long-term solvency. Second, banks might have also lowered lending standards to disburse the additional liquidity quickly, leading to a surge in bad loans. Third, loan defaults might have been exacerbated by a more economically challenging environment post disaster. Given, the significant damage caused by Tropical Cyclones Irma and Maria, the underlying economic environment in payout-receiving countries may have deteriorated faster than the control group, making debt repayment more difficult despite the payouts. I empirically test these hypotheses in the following sections.

4.2 Short-term Liquidity vs Long-term Solvency

In this section, I decompose the effects of the payouts on long-term solvency and short-term liquidity. Specifically, I utilize the dynamic event study model in equation (2) to examine whether the short-term effects of payouts translate into long-term stability. If the payouts do not address long-term solvency, I expect to see a deterioration in solvency indicators overtime and if they only address short-term liquidity then I expect to see a significant increase in liquidity indicators in the initial period around the payouts and deterioration in the following years.

I begin with the event study results for two solvency indicators, regulatory capital to risk-weighted assets and regulatory tier 1 capital to risk-weighted assets, which are displayed in Figure 3 and Figure 4. Both graphs, which report results that do not include the lagged dependent variable as a regressor, show a small initial decline in solvency in the 2 years following the payouts. This trend reverses in year 3, where there is a significant increase in both indicators. However, this improvement is not sustained as a downward trend emerges in the following years. The results suggest that the CCRIF payouts did not have a significant impact on long-term solvency overtime and may have been insufficient to resolve deeper solvency issues faced by banks in payout receiving countries. The results also suggest that banks drew down on their reserves for most of the post-payout period. Figure A23 and Figure A24 in online Appendix D, which report the results when the lagged dependent variable is included as a regressor using equation (3), show that the deterioration in the regulatory capital and regulatory tier 1 capital ratios was even more acute and persistent when past dynamics of these particular solvency indicators are factored in. To more completely represent the empirical evidence around long-term solvency, I also use equation (1) to conduct a difference-in-differences analysis. The results, presented in online Appendix C4, suggest that relative to banks in countries which did not receive a payout, banks in payout-receiving countries experienced a positive boost in their regulatory capital and regulatory tier 1 capital ratios as a result of the payouts. These effects were, however, not statistically significant, meaning that the observed differences could plausibly have occurred by chance and cannot be reliably attributed to the CCRIF payouts. Therefore, the overall interpretation is that CCRIF payouts were associated with some short-term gains in solvency indicators, but these gains were neither robust nor persistent enough to produce statistically verifiable long-term improvements in bank solvency. This supports the broader inference that payouts were likely insufficient to address fundamental solvency challenges faced by banks in the aftermath of the 2017 cyclones.

Insert Figure 3 here

Insert Figure 4 here

As it relates to short-term liquidity, the event study results for two liquidity indicators, liquid assets to total assets and liquid assets to short term liabilities are displayed in Figure 5

and Figure 6. Both graphs, which report results that do not include the lagged dependent variable as a regressor, show a significant increase in liquidity in the first year after the payouts, after which a striking downward trend emerges. The downturn in liquidity grows over time suggesting that the payouts were only sufficient to address short term liquidity issues. Figure A25 and Figure A26 in online Appendix D, which report the results when the lagged dependent variable is included as a regressor using equation (3), show similar increases in liquidity the year around the payouts but indicate that the downturn in liquidity in the proceeding years was actually much more severe when the effect of the past dynamics of liquidity is taken into consideration. As with the solvency indicators, I triangulate the empirical evidence by using equation (1) to conduct difference-in-differences analyses. The results, presented in online Appendix C5, suggest that relative to banks in countries which did not receive a payout, banks in payout-receiving countries recorded a significant difference in the average decline in their liquidity ratios over time. This provides ample support for the short-term liquidity hypothesis.

Insert Figure 5 here

Insert Figure 6 here

4.3 Credit Expansion vs Servicing NPLs

The initial boost and subsequent downturn in liquidity observed in Figure 5 and Figure 6 suggest that banks in payout receiving countries acted quickly to utilize the additional liquidity that flowed into the financial system as a results of the CCRIF payouts. Banks could have utilized this liquidity in one of two ways. Either to expand credit through increased issuance of new loans or to service non-performing loans. I use the event study model in equation (2) to examine the patterns in post-payout loan issuance and NPLs as a proportion of total loans to determine whether banks might have lowered lending standards to disburse the additional liquidity quickly, leading to a surge in bad loans or whether they focused on servicing NPLs.

The results for NPLs, displayed in Figure 7, shows a declining trend in NPLs as a proportion of total loans post-payout, suggesting that rather than disbursing the additional liquidity quickly through loan issuance, banks may have instead focused on servicing NPLs. NPLs as a proportion of total loans see reductions up to three years after the payouts and don't return to the pre-payout level until year four and five.

Insert Figure 7 here

The servicing of NPLs appears to have been complemented with a corresponding restriction in the credit made available to customers as the post-payout dynamics of the number of credit accounts and domestic credit to the private sector, shown in Figure 8 and Figure 9,

indicate that banks significantly reduced loan issuance until about year 3 when there is a sharp increase followed by another period of decline. Of note is the fact that despite the surge in loan issuance in year 3, the number of credit accounts remains substantially below the level it was at in both the payout year and the entire pre-payout period. Figure A27, Figure A28 and Figure A29 in online Appendix D, which report the results when the lagged dependent variable is included as a regressor using equation (3), show steeper trends in the decline of NPLs and the restriction of credit.

Insert Figure 8 here

Insert Figure 9 here

Additional insights into how ECCU banks managed the post-payout liquidity can be drawn from the sectoral distribution of loans. As shown in Table A6 and Table A7 of online Appendix C6, banks did not increase lending to the financial sector, where credit typically circulates quickly through secondary intermediation. Instead, the results reveal a statistically significant increase in lending to the non-financial sector post-payout. However, the scale of the increase in non-financial sector loans is modest relative to the overall contraction observed in the number of credit accounts and domestic credit to GDP. This suggests that while some selective lending occurred, banks largely refrained from broad-based credit expansion. Instead, they appear to have rationed credit, tightening loan issuance criteria and directing the limited new lending toward borrowers perceived as lower risk or strategic, rather than engaging in widespread credit creation. This sectoral pattern of credit allocation is consistent with a mechanism where banks, faced with elevated post-disaster risks and weakened borrower balance sheets, prioritised protecting asset quality over pursuing aggressive lending strategies. Thus, the restricted and selective expansion of credit to the non-financial sector complements the evidence of loan write-offs and declining capital buffers, reinforcing the interpretation that banks acted conservatively with the liquidity inflows from CCRIF payouts, using them mainly to stabilize balance sheets rather than expand credit.

Banks can service NPLs in several ways, the primary methods being through pursing borrowers to resume payment (i.e. loan curing) or writing off the loans. The sharp decline in NPLs after year 0 does not appear to be the result of genuine repayment (loan curing) because If loans were curing, capital ratios should improve and remain stable or grow, as improved loan performance boosts retained earnings and lowers risk-weighted assets. Instead, as shown in Figure 8 and Figure 9, capital remains suppressed in years 4–5, which suggests that banks may have been writing off loans, absorbing losses that reduce capital and struggling to generate income after the temporary liquidity boost faded.

4.4 Faster Economic Deterioration

To test whether the underlying economic environment in payout-receiving countries deteriorated faster than the control group, I use equation (1) to conduct a difference-in-differences analysis. The graphical results, shown in Figure 10, provide no support for this hypothesis. GDP growth for payout-receiving countries rises above that of non-payout countries post-payout, suggesting that the payouts may have provided an immediate economic boost and mitigated a greater decline in economic conditions than would otherwise have occurred.

Insert Figure 10 here

Although GDP growth deteriorated substantially in payout-receiving countries following the 2017 cyclones, the evidence suggests that this deterioration was not faster than that of the control group. Instead, CCRIF payouts appear to have mitigated the severity of the economic contraction relative to non-recipient countries. This is consistent with a view that payouts provided critical liquidity that softened the economic shock, even though they did not entirely avert a downturn.

To present more fulsome evidence of the post-payout dynamics of GDP growth in payout-receiving countries, I also estimate dynamic treatment effects using the event study specification in equation (2). The results, shown in Figure A15 of online Appendix C7, indicate that GDP growth initially collapsed in the aftermath of the cyclones despite payouts but recovered strongly in later years (by year 4–5 post-payout). This suggests that CCRIF payouts may not have been large enough to prevent an initial contraction in GDP growth (years 1–3 after the disasters) but may have contributed to a stronger and faster economic recovery once the immediate shock dissipated.

The Caribbean as a whole experienced approximately US$130 billion in losses across 18 countries due to the 2017 hurricane season. The event study results for GDP growth in payout-receiving countries can be partly explained by the fact that, in contrast to these significant losses, CCRIF made payouts totaling only US$62 million in 2017, with some countries like Antigua and Barbuda, Anguilla, and St. Kitts & Nevis receiving relatively small amounts. The total payouts in 2017 represent a mere 0.048% of the estimated losses. In keeping with expectations that this quantum of payouts would be insufficient to generate a significant economic impact given the scale of the economic losses, the difference-in-differences regression results, presented in Table A8 of online Appendix C7, show that the effect of payouts on GDP growth was positive but statistically imprecise. In both regressions (columns 1 and 2), the coefficient on Treat $\times$ Post is positive (0.651 and 1.765 respectively), suggesting that payouts may have boosted GDP growth relative to countries that did not receive payouts. However, the standard errors are large relative to the point estimates, and the effects are not statistically significant at conventional levels.

Taken together, the pieces of evidence across the short-term liquidty, credit expansion and faster economic deterioration hypotheses suggest that while CCRIF payouts provided much-needed short-term liquidity in the immediate aftermath of Tropical Cyclones Irma and Maria, they were ultimately insufficient to restore long-term financial stability in payout-receiving countries. Banks used the liquidity prudently—focusing on servicing existing non-performing loans rather than expanding new credit—but this came at the expense of capital adequacy. The drawdown of reserves to manage legacy loan defaults meant that even as NPL ratios improved temporarily, the overall level of NPLs net of provisions remained high, leaving banks more vulnerable. Importantly, this deterioration cannot be explained by differences in macroeconomic conditions, as payout-receiving countries experienced stronger GDP growth than their counterparts. The findings highlight a critical distinction: while insurance-based payouts can alleviate liquidity pressures in the short term, they do not necessarily resolve deeper solvency challenges, especially in banking systems already burdened by weak asset quality prior to the shock.

4.5 CCRIF Payouts and Bank Profitability

To shed light on the mechanisms driving the short-term liquidity hypothesis whereby banks in payout-receiving countries utilized the liquidity from CCRIF payouts to service NPLs rather than expand credit and rebuild capital buffers - despite a slightly more favourable economic environment than their peers in comparator countries - I examine how this prudential action affected their profitability and operational costs. I ground this examination of profitability and operational efficiency in the large banking literature which shows that servicing NPLs imposes significant operational costs on banks, especially through monitoring, recovery efforts, and balance sheet strain (Berger and DeYoung, 1997; Ghosh, 2015; Phung et al., 2022; Zamore et al., 2023). I am particularly interested in testing for what Berger and DeYoung (1997) called the "bad luck" hypothesis, where NPLs arise from external shocks and create operational inefficiencies due to higher servicing costs. To do this I conduct a decomposition of the effects of the payouts on both interest margin to gross income and non-interest expenses to gross income using the dynamic event study model in equation (2). The results for interest margin to gross income are shown in Figure 11 while the results for non-interest expenses to gross income are shown in Figure 12.

Insert Figure 11 here

Insert Figure 12 here

Figure 11, which reports results that do not include the lagged dependent variable as a regressor, shows a clear decline in interest margin starting well before the CCRIF payouts (year 0), with a steady downward trend from year –8 through to year +5. Interest margin falls below the long-run average after year +3 and continues to decline. This suggests profitability from core lending operations steadily deteriorated, even after the CCRIF liquidity event.

There is no sign of margin recovery post-payout, which would be expected if banks used the liquidity to expand credit portfolios and generate more interest income. Instead, banks appear to maintain tight credit conditions, consistent with servicing old risk rather than underwriting new risk.

Figure 12, which reports results that do not include the lagged dependent variable as a regressor, shows an initial decline in non-interest expenses relative to gross income after the CCRIF payouts, with a pronounced increase from year +3 to year +5; the ratio peaks sharply in year +5. This indicates rising operational costs, particularly in the medium-to-long run.

The decline in interest margin and concurrent rise in non-interest expenses after the payouts are clear signals of operational inefficiency and profitability strain. Rather than providing lasting support for lending and capital, the liquidity from CCRIF payouts appears to have been consumed by the costs of servicing NPLs—with little impact on rebuilding sustainable profitability; this is precisely what the "bad luck" hypothesis predicts (Berger and DeYoung, 1997), as exogenous shocks raise the volume of distressed loans, and banks must devote additional operational resources to managing the fallout, leading to long-term inefficiencies in profitability. As with previously examined indicators, Figure A32 and Figure A33 in online Appendix D, which report the results when the lagged dependent variable is included as a regressor using equation (3), show steeper trends in the strain on profitability and the erosion of operational efficiency over the medium-to-long-term. I round out presentation of the empirical evidence on the profitability mechanism by using equation (1) to conduct difference-in-differences analyses. The results, presented in online Appendix C8, suggest that relative to banks in countries which did not receive a payout, banks in payout-receiving countries recorded a significant difference in the average decline in their interest margins over time. While the estimates for the difference in the average increase in non-interest expenses were in the positive direction, this difference was not statistically significant at conventional levels.

To deepen understanding of the mechanisms and to explore whether the effects of CCRIF payouts were driven by banks with weaker balance sheets, I exploit heterogeneity in pre-treatment asset quality by splitting the sample based on whether banks had above-median NPL ratios in the year preceding the payout. The results from the dynamic event study decomposition, presented in Appendix C9, provide clear evidence of differential responses. Among weaker banks, interest margins to gross income declined sharply from year +2 onward, while non-interest expenses rose steadily, culminating in a pronounced spike by year +5. In contrast, stronger banks exhibited stable or modestly improving margins and a relatively flat operational cost trajectory. These patterns are consistent with the "bad luck" hypothesis (Berger and DeYoung, 1997), in which banks experiencing exogenous shocks allocate post-crisis liquidity toward servicing distressed loans—incurring higher monitoring and recovery costs—rather than toward new lending or profitability-enhancing activities.

5 Concluding Discussion

The findings of this study provide important new insights into the role of sovereign catastrophe risk pooling in supporting financial stability in small island developing states (SIDS), using the Eastern Caribbean Currency Union (ECCU) and the 2017 CCRIF payouts as a quasi-experimental setting. The study also introduces and empirically examines a novel mechanism of financial intermediation: insurance-driven liquidity following sovereign catastrophe risk pooling. Unlike traditional liquidity shocks originating from monetary policy interventions or deposit flows, insurance payouts under sovereign risk pools inject liquidity into the economy indirectly through government fiscal responses and borrower cash flows. I show that while this exogenous liquidity boost initially strengthens bank liquidity positions, it does not restore long-term solvency. Instead, banks use the inflow defensively to stabilise existing non-performing loans, at the cost of capital drawdown, profitability erosion, and persistent financial vulnerability. These findings deepen our understanding of how the source, structure, and transmission channel of liquidity shocks critically shape financial stability outcomes in disaster-exposed economies.

Specifically, I document a paradoxical dynamic: although banks in payout-receiving countries used the additional liquidity prudently to service non-performing loans (NPLs), the decline in NPLs was offset by a sharper drawdown in capital provisions. As a result, NPLs net of provisions rose substantially, leaving banks in a weaker financial position compared to their counterparts in non-payout countries. This deterioration in capital buffers, despite prudent liquidity management, highlights a key limitation of catastrophe insurance as a financial stabilisation tool: liquidity support alone cannot resolve underlying asset quality and solvency vulnerabilities.

The analysis further demonstrates a clear distinction between short-term liquidity effects and long-term solvency outcomes. Liquidity ratios improved significantly in the immediate aftermath of the payouts, but these gains were short-lived, with liquidity metrics declining sharply in subsequent years. Solvency indicators, such as regulatory capital and Tier 1 capital ratios, showed no statistically significant or persistent improvement, reinforcing the interpretation that CCRIF payouts served primarily as temporary liquidity cushions rather than instruments of structural financial repair.

A crucial mechanism underlying these outcomes is the prioritisation of legacy risk management over credit expansion. Banks largely restricted new lending for several years post-payout, choosing instead to stabilise existing portfolios by reducing exposure to new credit risks. While this defensive strategy helped contain further deterioration in loan quality, it came at the cost of subdued credit supply to the private sector, which likely constrained the broader economic recovery. Banks also did not increase lending to the financial sector, where credit typically circulates quickly through secondary intermediation.

Moreover, the study uncovers persistent declines in bank profitability and operational efficiency following the payouts. Interest margins eroded steadily, while non-interest expenses rose over time — effects that were most pronounced among banks with weaker pre-shock balance sheets. These findings align with the "bad luck" hypothesis (Berger and DeYoung, 1997), illustrating how exogenous shocks impose enduring operational strains through elevated NPL servicing costs and balance sheet repair efforts.

In sum, the evidence suggests that while sovereign catastrophe risk pooling mechanisms such as CCRIF are highly effective at mitigating immediate liquidity pressures and averting acute financial crises, they are not sufficient on their own to secure long-term financial sector stability in highly vulnerable economies. Insurance-based liquidity injections, although valuable, cannot substitute for deeper capital strengthening, risk management improvements, and resilience-building measures in the banking system.

For policymakers, these results imply that sovereign catastrophe pools should be complemented with parallel initiatives aimed at bolstering long-term financial resilience. These might include building stronger countercyclical capital buffers, enhancing supervisory frameworks for asset quality, and developing targeted recovery facilities for post-disaster bank recapitalisation. Particularly in SIDS and other disaster-prone, economically concentrated regions, disaster risk financing strategies must evolve beyond liquidity provision to encompass the broader solvency and profitability dimensions necessary for sustained financial sector stability.

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Figure 1: This figure provides parallel trends for the single treatment DiD regression which compares the nonperforming loans net of capital provisions of ECCU banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not.Banks in countries which received a CCRIF payment are assigned to the treated group (represented by red line) and banks in countries which did not are assigned to the control group (represented by the blue line).

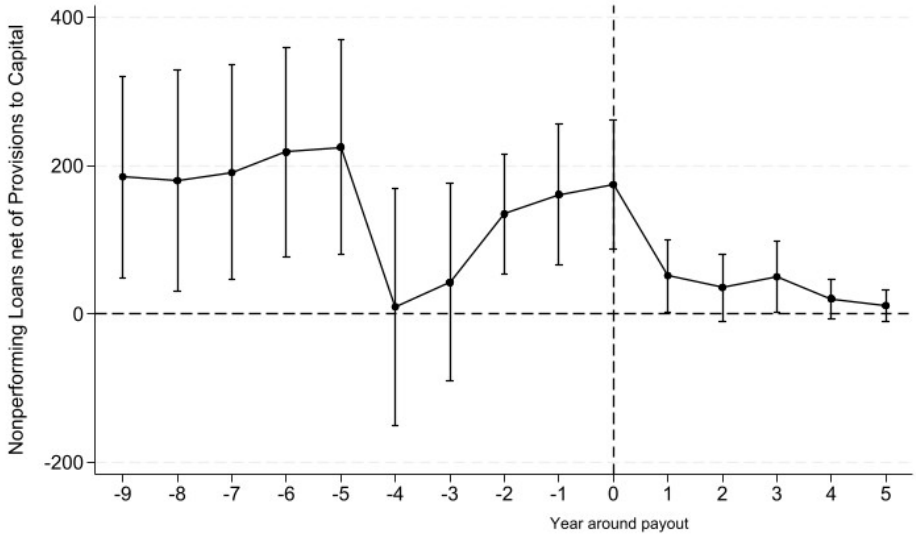


Figure 2: This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the nonperforming loans net of capital provisions of ECCU banks in countries which received a CCRIF insurance payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

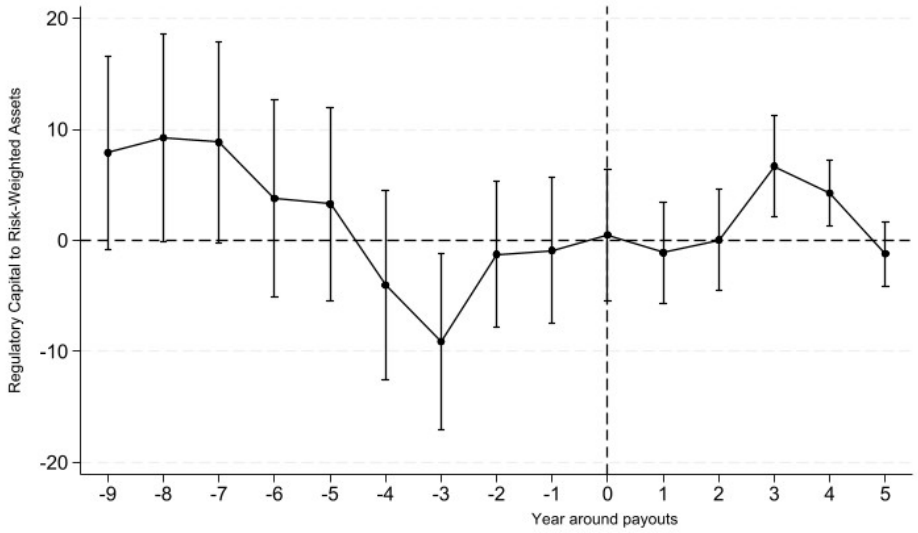


Figure 3: This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the regulatory capital to risk-weighted assets ratio of ECCU banks in countries which received a CCRIF insurance payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

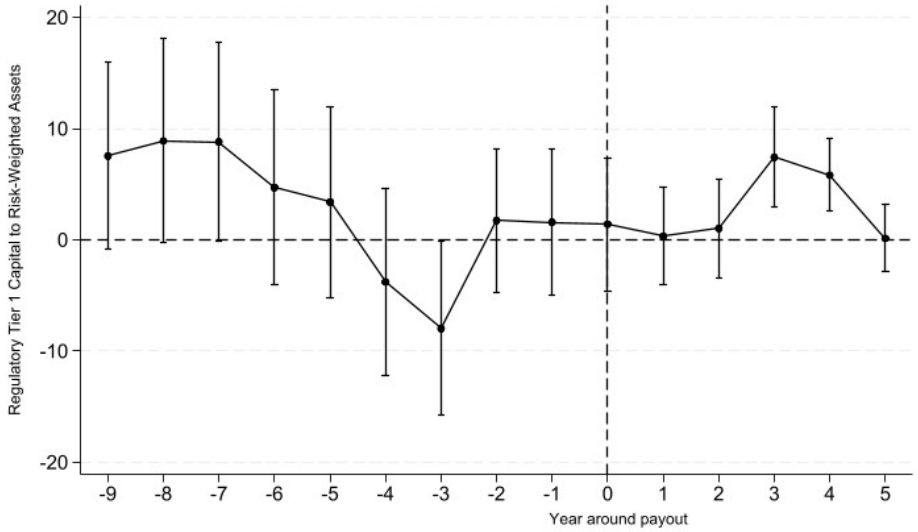


Figure 4: This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the regulatory tier 1 capital to risk-weighted assets ratio of ECCU banks in countries which received a CCRIF insurance payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

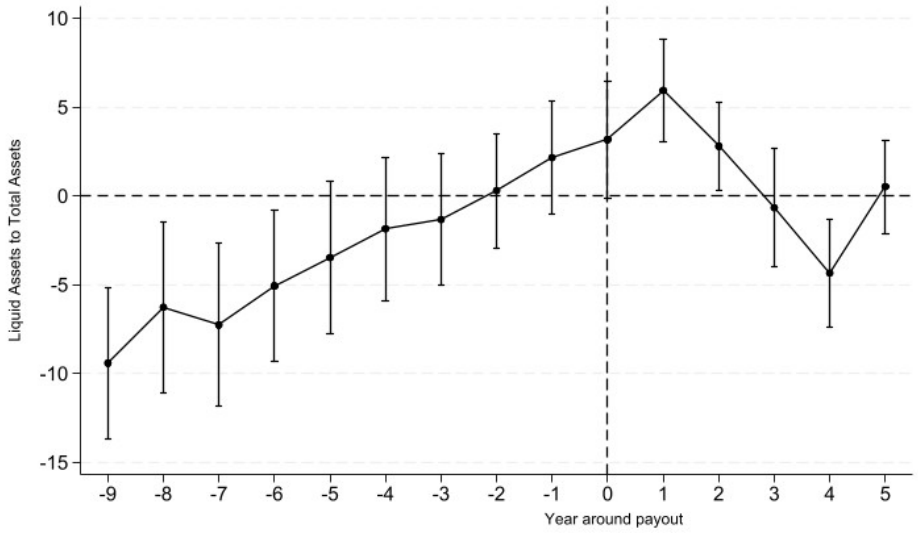


Figure 5: This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the liquid assets to total assets ratio of ECCU banks in countries which received a CCRIF insurance payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

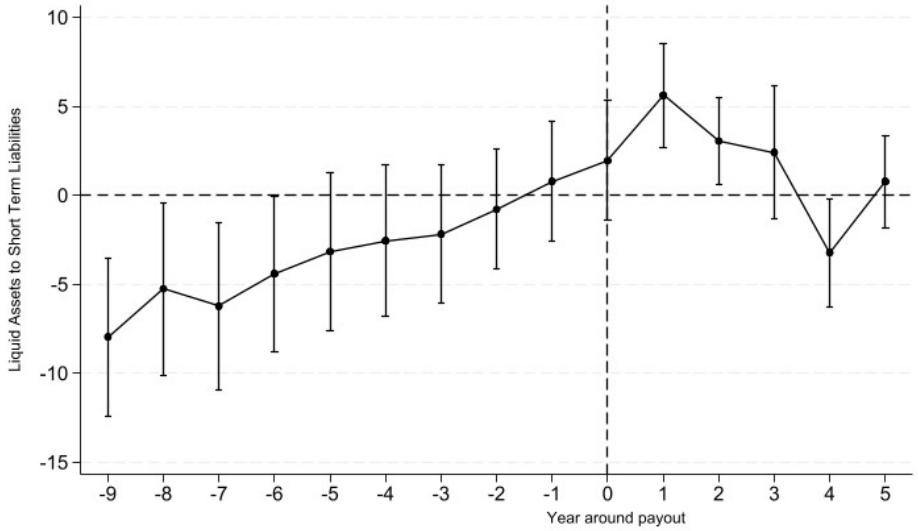


Figure 6: This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the liquid assets to short term liabilities ratio of ECCU banks in countries which received a CCRIF insurance payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

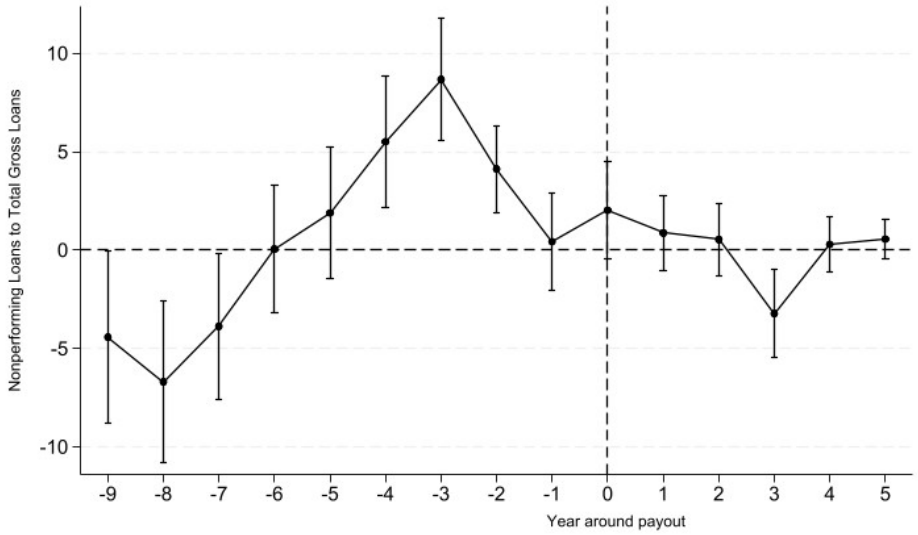


Figure 7: This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the NPLs to total loans ratio of ECCU banks in countries which received a CCRIF insurance payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

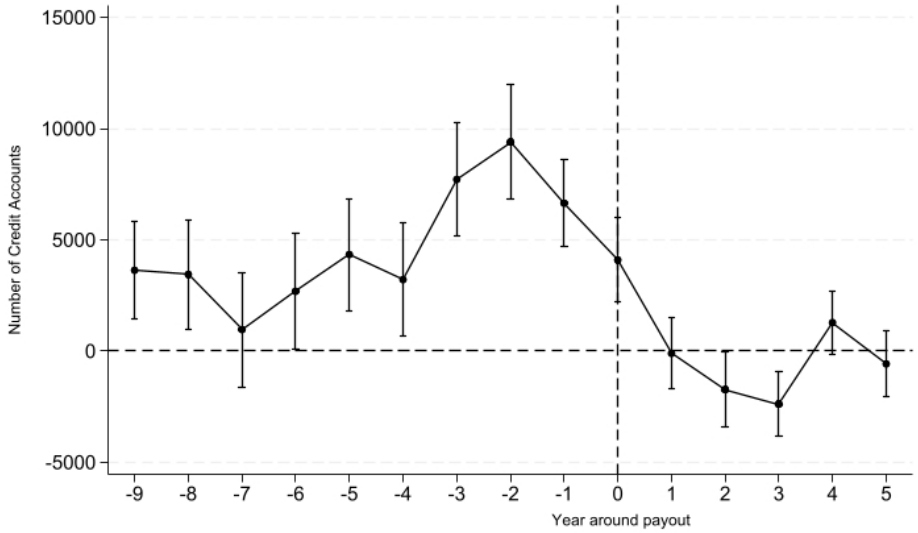


Figure 8: This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the number of credit accounts issued by ECCU banks in countries which received a CCRIF insurance payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

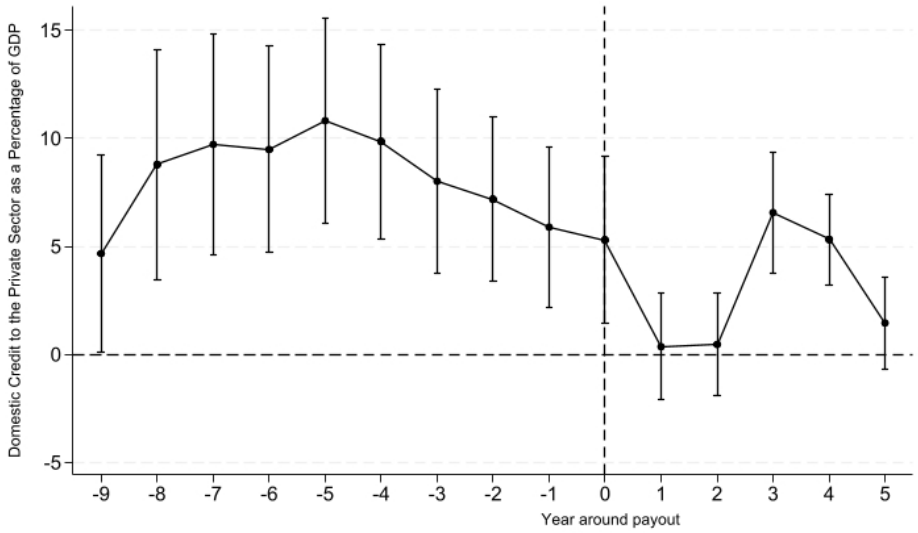


Figure 9: This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the domestic credit to the private sector as a percentage of GDP of countries which received a CCRIF insurance payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

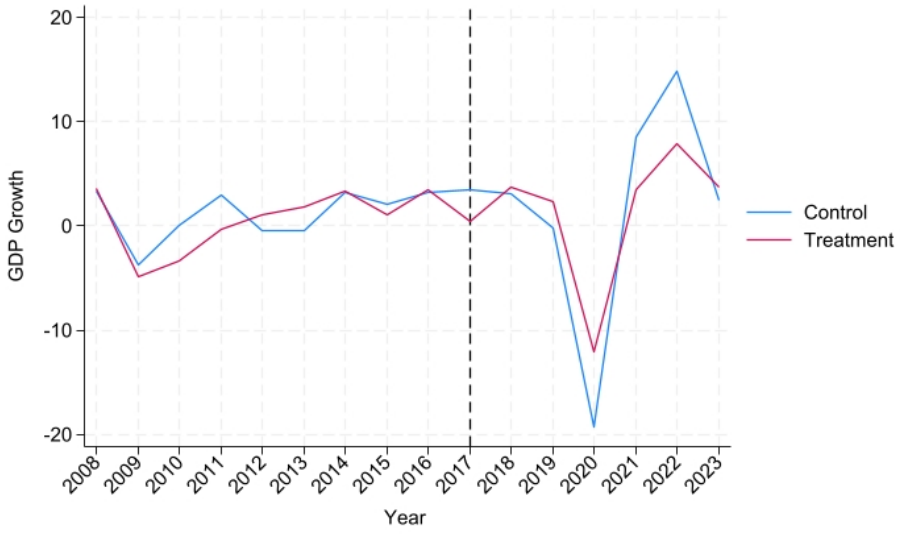


Figure 10: This figure provides parallel trends for the single treatment DiD regression which compares the GDP growth of countries which received a CCRIF insurance payout in 2017 to those which did not.Countries which received a CCRIF payment are assigned to the treated group (represented by red line) and countries which did not are assigned to the control group (represented by the blue line).

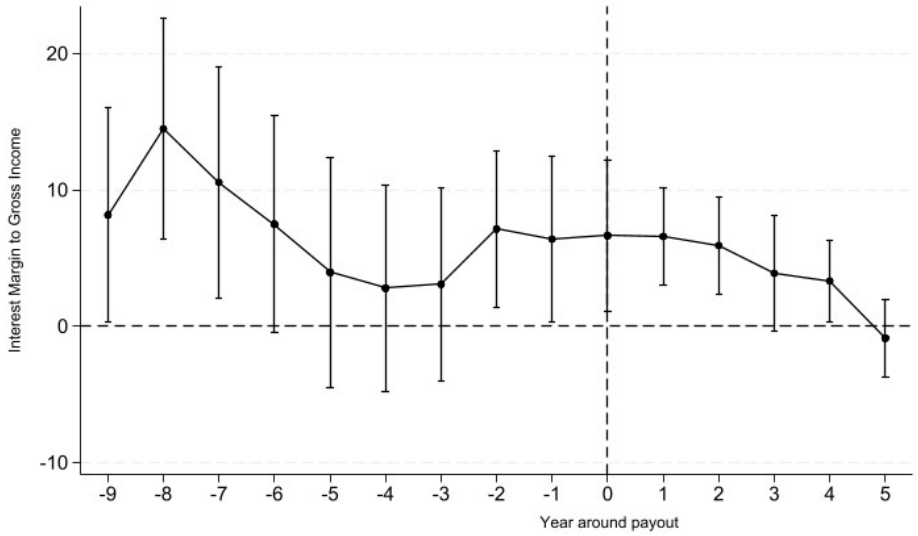


Figure 11: This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the interest margin to gross income ratio of ECCU banks in countries which received a CCRIF insurance payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

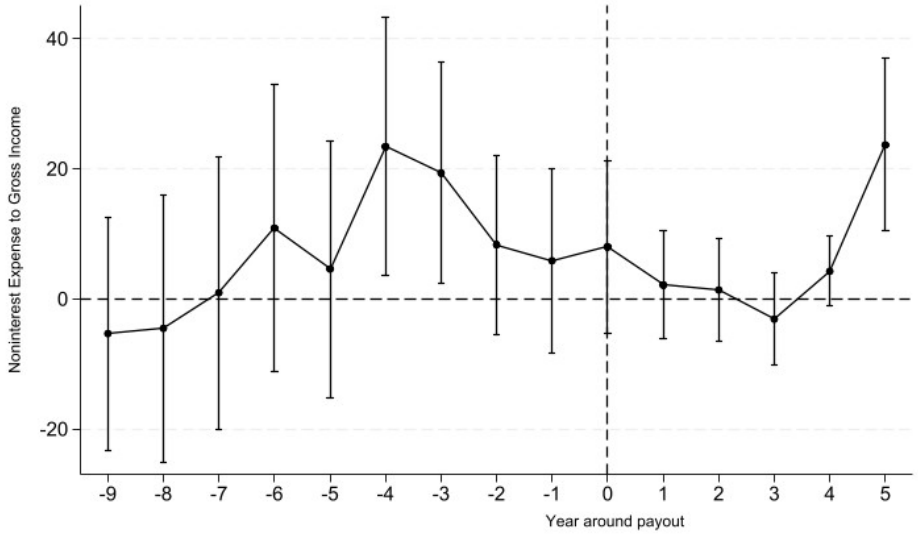


Figure 12: This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the non-interest expense to gross income ratio of ECCU banks in countries which received a CCRIF insurance payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Table 1: **Variable Definitions**. This table presents definition of the variables utilized in the empirical analysis.

Variables	Definitions
Catastrophe Risk Insurance Variables	
CCRIF Payout Rate	Annual rate at which CCRIF makes catastrophe insurance payouts to its member countries calculated as the percentage of the annual payout relative to the average annual payout over the period
Financial Stability Measures	
Nonperforming Loans Net of Capital Provisions	Financial stability inidctaor which measures capacity of bank capital to withstand looses from NPLs
Regulatory Capital to Risk-Weighted Assets	Financial stability inidctaor which measures capital adequacey of deposit takers
Regulatory Tier 1 Capital to Risk-Weighted Assets	Financial stability inidctaor which compares a bank's equity capital with its total risk-weighted assets
Liquid Assets to Total Assets	Financial stability indicator which indicates the liquidity available to meet demands for cash
Liquid Assets to Short Term Liabilities	Financial stability indicator which indicates the liquidity mismatch between assets and liabilities
Nonperforming Loans to Total Gross Loans	Financial stability indictor which measures the quality of loans in a bank's loan portfolio
Number of Credit Accounts	Financial stability inidcator which measures number of loans issued
Domestic Credit to the Private Sector (% GDP)	Financial resources provided to the private sector by banks and other financial institutions
Disaster Control Variables	
Disaster Events	Number of disaster events in a given year
Monetrary Survey Control Variables	
Net Foreign Assets	The difference between a country's foreign assets and liabilities
Broad Money Liabilities M2	Measure of a country's money supply; indicates liquidity position of financial sector
Claims on Private Sector	Gross credit lent to individuals and enterprises; indicates credit risk and availability
Economic Environment Control Variables	
Inflation CPI	Measure of end of period inflation rate within the ECCU currency union
Real Effective Exchange Rate	Index of real effective exchange rate within each country (base year 2001)
Short Term Interest Rates	Weighted Average Interest Rate on all T Bills issued by the ECCB
Long Term Interest Rates	Weighted Average Interest Rate on all bonds issued by the ECCB
Official Development Assistance	Grants and external financial support received by each county in a given year

Table 2: **Summary Statistics**. This table provides summary statistics which describe the distribution of the main variables of interest.

Variables	N	Mean	SD	P25	Median	P75
Catastrophe Risk Insurance Variables						
CCRIF Payout Value	528	16.50M	18.90M	1.20M	7.33M	28.00M
CCRIF Payout Rate	528	100.00	114.57	7.27	44.35	169.52
Number of Payouts	528	3.88	3.89	0.50	3.50	5.50
Financial Stability Measures						
Nonperforming Loans Net of Capital Provisions	528	37.44	167.63	24.66	42.55	77.42
Regulatory Capital to Risk-Weighted Assets	528	19.54	10.33	14.31	18.80	23.39
Regulatory Tier 1 Capital to Risk-Weighted Assets	528	17.13	10.18	76.07	16.66	21.53
Liquid Assets to Total Assets	528	40.95	12.71	33.87	41.05	47.83
Liquid Assets to Short Term Liabilities	528	45.90	14.02	39.07	46.14	53.39
Nonperforming Loans to Total Gross Loans	528	11.63	7.06	7.38	10.03	14.45
Number of Credit Accounts	528	27532.27	13071.74	19374.00	26131.00	37088.00
Domestic Credit to the Private Sector (% GDP)	528	53.83	22.00	47.10	53.72	63.63
Disaster Control Variables						
Disaster Events	528	2.19	1.705	0.50	2.50	3.00
Monetrary Survey Control Variables						
Net Foreign Assets	528	742.13	996.47	114.12	599.25	1443.37
Broad Money Liabilities M2	528	2477.15	986.96	1643.47	2691.25	3211.14
Claims on Private Sector	528	1895.83	1011.21	1109.12	1671.96	2466.84
Economic Environment Control Variables						
Inflation CPI	528	2.72	5.26	-0.66	1.70	2.67
Real Effective Exchange Rate	528	93.73	6.97	89.54	91.96	95.4
Short Term Interest Rates	528	3.53	0.847	2.83	3.39	3.98
Long Term Interest Rates	528	6.82	0.46	6.47	6.95	7.08
Official Development Assistance	528	49.04	40.62	22.86	41.54	66.69

Table 3: **CCRIF Payout and NPLs Net of Capital Provisions**. This table reports DiD estimates for the differentail impact of CCRIF payouts on NPLs Net of Capital Provisions for financial institutions in countries which received a payout after the passage of Tropical Cyclones Irma and Maria in 2017 compared to those which did not. Year, disaster and saturated financial institution, country, ECCU currency union and ECCB regulatory supervision fixed effects are included. Standard errors are double clustered by financial institution-year.*** p < 0.01, ** p < 0.05, * p < 0.1.

	NPLs Net of Capital Provisions	
	(1)	**(2)**
Treat * Post	107.7***	122.8***
	(5.49)	(33.472)
Net Foreign Assets		0.008
		(0.028)
Broad Money Liabilities M2		0.085
		(0.049)
Claims on Private Sector		0.039
		(0.043)
Real Effective Exchange Rate		1.575
		(3.255)
Official Development Assistance		0.259
		(0.137)
Constant	12.97	-440.70
	(1.28)	(343.094)
Adjusted R-squared	0.131	0.142
Year FE	Yes	Yes
Financial Institution (FI) FE	Yes	Yes
Disaster FE	No	Yes
FI x Country x ECCU x ECCB FE	No	Yes
N	528	528

Online Appendix for Financial Intermediation of Insurance-Driven Liquidity: Evidence from Sovereign Climate Risk Pools

A. Data Appendix

A.1 ECCB Database

The Eastern Caribbean Central Bank (ECCB) maintains a comprehensive Monetary and Financial Statistics Database to monitor and analyze the financial health of its member countries. These data provide insights into the liquidity, stability, and performance of the financial system within the Eastern Caribbean Currency Union (ECCU). In addition to a high-level overview of the banking system's monetary aggregates, a granular breakdown of sectoral credit distribution (households, businesses, government) and commercial bank liabilities/assets are provided in the detailed monetary survey. The aggregate balance sheets of banks includes data on loans, investments, cash reserves and customer deposits. Focused metrics on key financial indicators for individual banks, such as liquidity ratios or non-performing loans (NPLs) is also provided in section of the database dedicated to tracking five distinct categories of financial stability relating to capital adequacy, asset quality, profitability, liquidity and market risk. I accessed the data directly from the ECCB website. The data extract used in this study was downloaded on October 30, 2024.

A.2 CCRIF Payout Data

The Caribbean Catastrophe Risk Insurance Facility Segregated Portfolio Company (CCRIF SPC) provides parametric insurance payouts to member countries in response to natural disasters, with data publicly available on its website. This dataset documents payouts from June 2007 to July 2025, detailing disbursements triggered by tropical cyclones, earthquakes, excess rainfall, and specialized policies (e.g., COAST fisheries, electric utilities). For Eastern Caribbean Currency Union (ECCU) countries, the data includes payout amounts, frequency, and policy types, offering insights into climate risk financing mechanisms.

ECCU members received frequent payouts, reflecting regional vulnerability. Grenada's $42.4 million for Tropical Cyclone Beryl in 2024 is the largest payout made to date. Data was collected manually from CCRIF's payout tables, updated post-disaster. The webpage organizes payouts in tabular format, sorted by event date, country, and policy type. Payouts occur within 14 days of an event, ensuring rapid liquidity. While the dataset includes non-ECCU nations (e.g., Nicaragua, Belize), the focus on ECCU highlights how parametric insurance mitigates fiscal shocks from climate disasters in Small Island Developing States (SIDS). The dataset spans 16 years (2008–2023), covering all ECCU countries that received payouts.

B. Theoretical Model for the Transmission Mechanism of CCRIF Payouts in the ECCU

Pathway 1: Liquidity Injection and Economic Recovery

Let P represent the CCRIF payout received by the government in the event of a disaster. The payout P is a one-time liquidity injection intended to stimulate economic recovery by funding public services, infrastructure repair, and other recovery initiatives. We assume a multiplier effect m such that $m > 1$.

1. **Liquidity Injection:** The government uses P to fund disaster recovery activities. The economic impact of this spending is magnified by the multiplier m:

$$\text{Total Economic Impact} = P \times m$$

2. **Resulting Income Increase:** The increased spending (Total Economic Impact) stimulates economic activity, raising income for households and businesses. Let Y represent the total income generated from the payout:

$$Y = P \times m$$

3. **Proof of Economic Recovery:** As income Y rises, economic recovery is stimulated, which positively affects employment, consumption, and production in the disaster-affected region. Thus, the CCRIF payout P indirectly contributes to economic stability through Y.

Since economic recovery Y is proportional to P, this model supports the theoretical claim that CCRIF payouts promote recovery through a multiplier effect.

Pathway 2: Financial Intermediation

Now, let us consider the transmission of income Y through the financial intermediation process, where banks and financial institutions play a role in distributing this liquidity.

1. **Bank Deposits from Income Increase:** Assume a portion α of income Y is deposited in financial institutions. Thus, the deposits D are given by:

$$D = \alpha \times Y = \alpha \times (P \times m)$$

2. **Lending Capacity:** Banks use deposits D to extend loans. Given a reserve ratio r (where $r < 1$), the lending capacity L of financial institutions is:

$$L = \frac{D}{r} = \frac{\alpha \times P \times m}{r}$$

3. **Proof of Financial Intermediation:** The lending capacity L increases with the CCRIF payout P. This theoretical model suggests that higher levels of government spending from P boost bank deposits D and, consequently, loan issuance L. Therefore, the CCRIF payout indirectly raises the lending capacity of financial institutions through the process of financial intermediation.

Pathway 3: Financial Stability through Debt Servicing and Asset Quality Improvement

Finally, we demonstrate how increased lending capacity L and economic recovery Y contribute to financial stability by supporting debt servicing and reducing non-performing loans (NPLs).

1. **Debt Servicing Capacity:** Let the proportion β of income Y be used by households and businesses to service debt. Then, the debt servicing capacity S is:

$$S = \beta \times Y = \beta \times (P \times m)$$

2. **Impact on Non-Performing Loans:** Let NPL represent the proportion of loans that are non-performing. An increase in debt servicing capacity S reduces NPL as borrowers are more able to meet their obligations:

$$\Delta NPL = -\gamma \times S = -\gamma \times (\beta \times P \times m)$$

   where γ is a coefficient representing the sensitivity of NPL to debt servicing capacity.

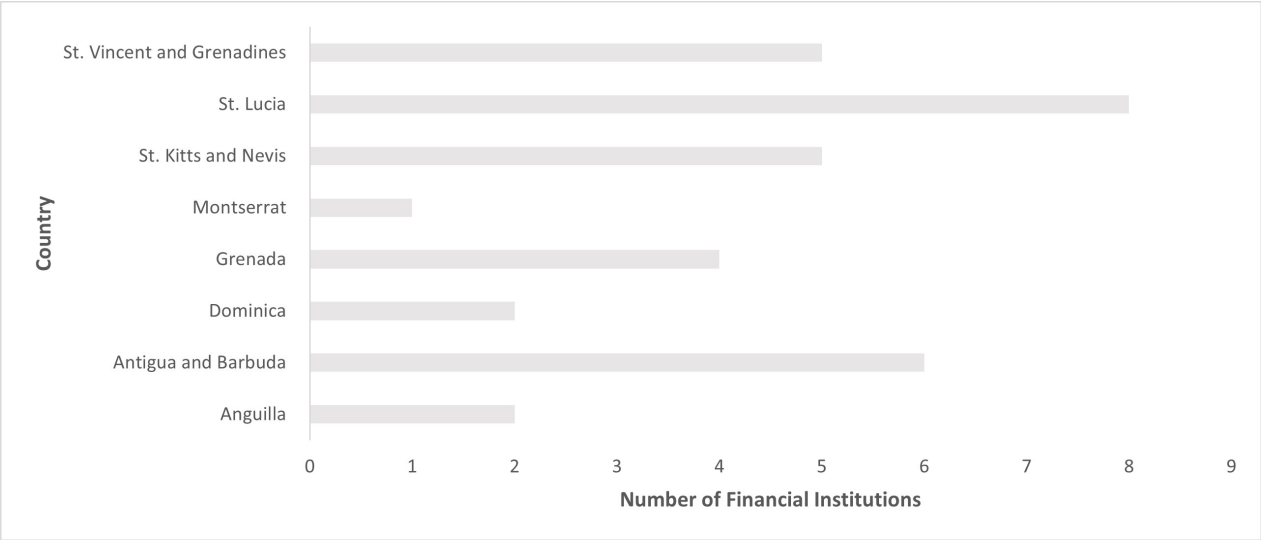
3. **Proof of Financial Stability:** As S increases due to the income boost from Y, the level of non-performing loans NPL decreases. This strengthens the balance sheets of financial institutions, contributing to higher asset quality and financial stability.

Therefore, through debt servicing and asset quality improvement, the transmission mechanism of CCRIF payouts is shown to support financial stability. The theoretical model demonstrates that, in a financialized and integrated economy like the ECCU, CCRIF payouts should ultimately reduce financial strain on banks by increasing the economy's debt servicing capacity.

C. Appendix Figures and Tables

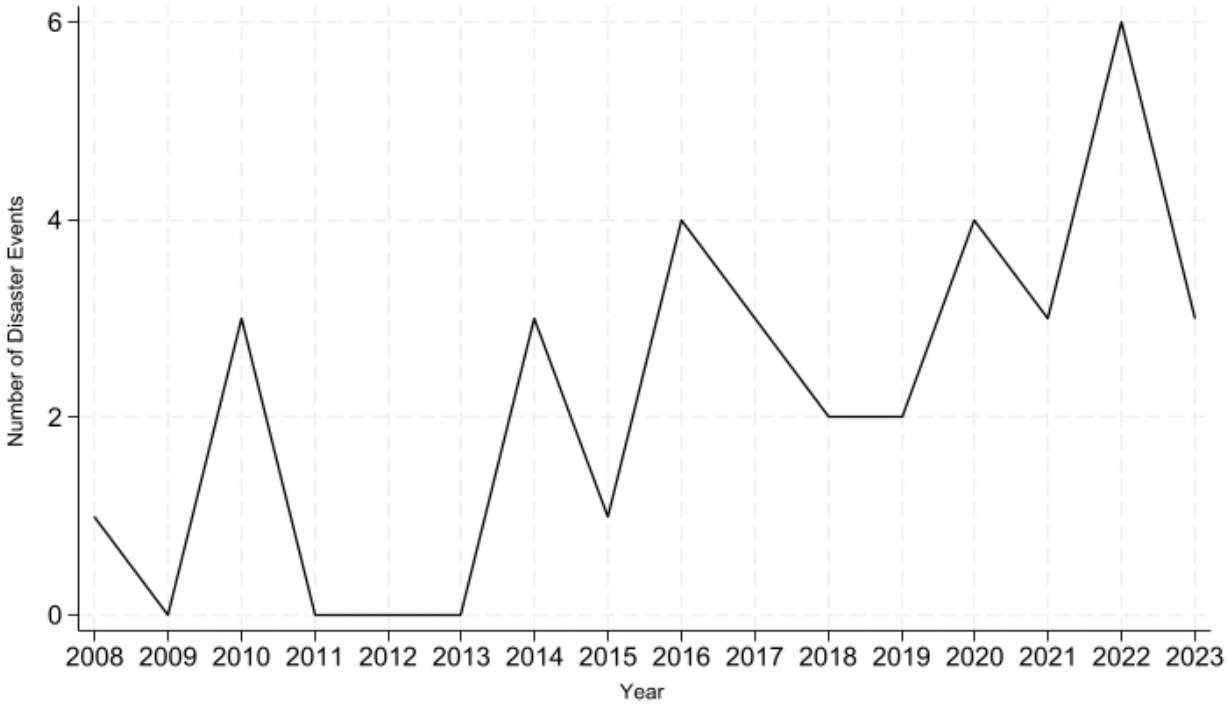
C.1 Descriptive Statistics for ECCU Banks, Disaster Events and Payouts

Figure A1: Number of ECCU Banks per Country



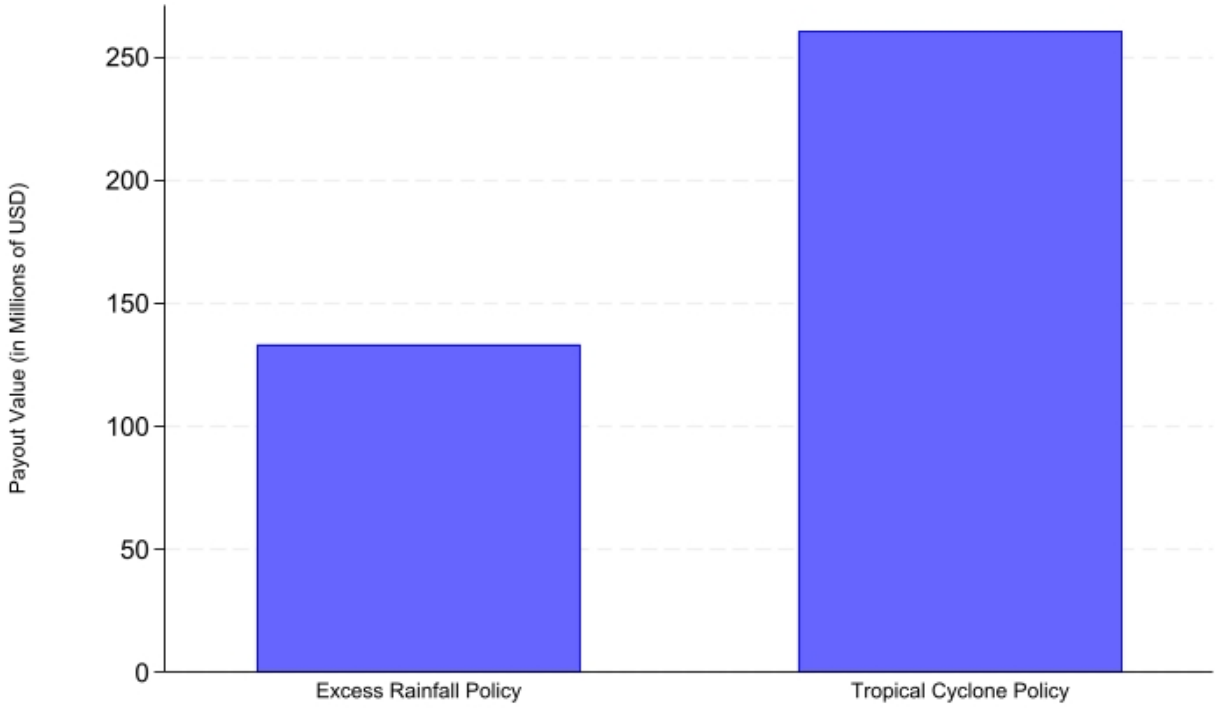
This figure shows the country distribution for the 33 banks which operate within the ECCU.

Figure A2: Number of Disaster Events Within the Eastern Caribbean



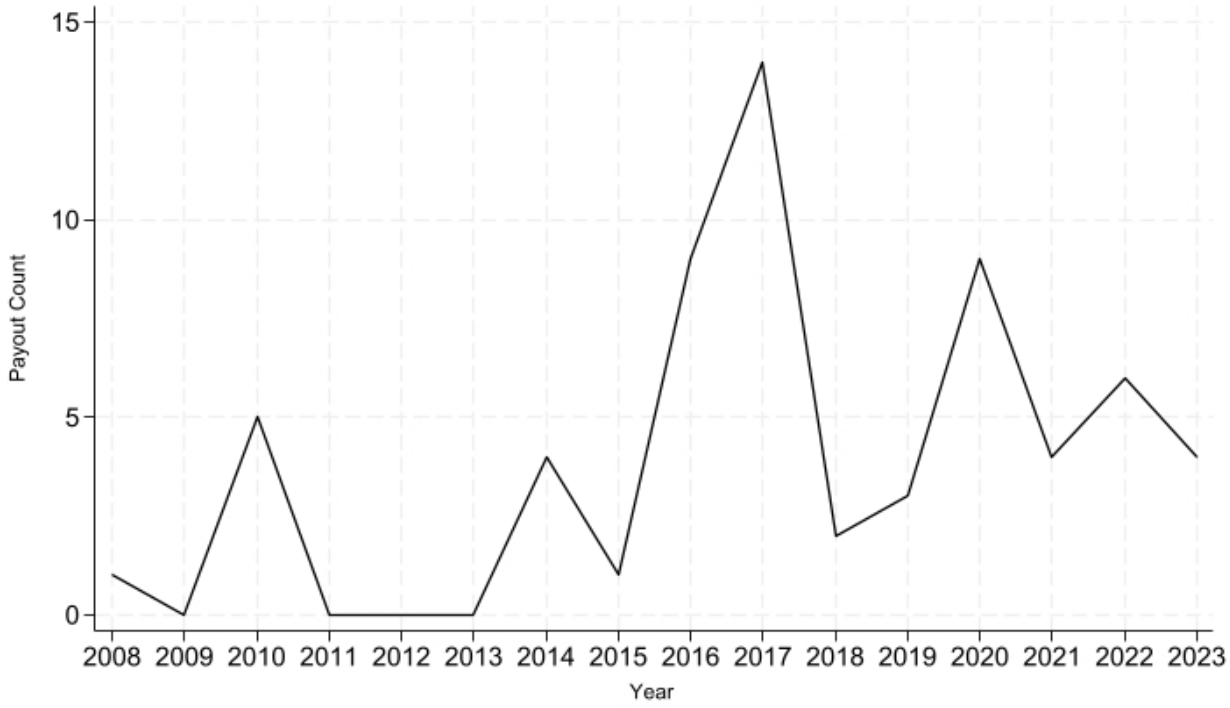
This figure shows the growth in the number of disaster events that affected the small island developing states within the Eastern Caribbean over the 2008-2023 period.

Figure A3: Payout Value for CCRIF's Excess Rainfall and Tropical Cyclone Policies



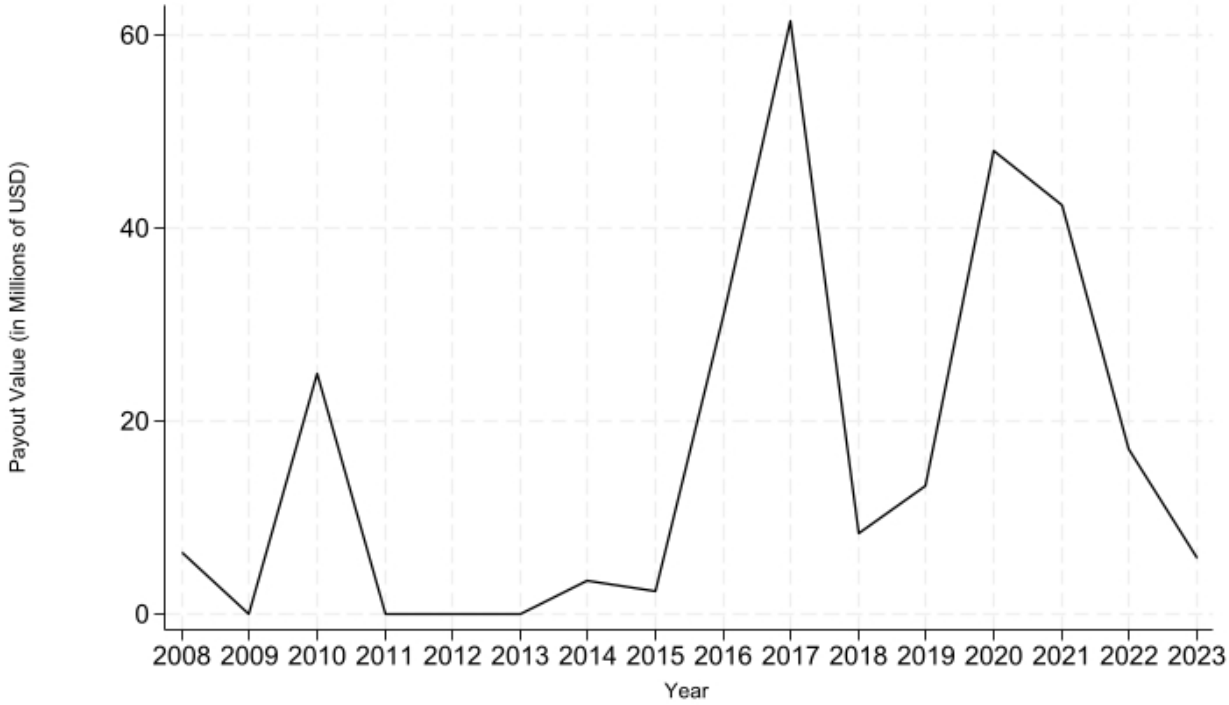
This figure shows the total value of payouts made to CCRIF member countries for the excess rainfall policy and the tropical cyclone policy over the 2008-2023 period.

Figure A4: Number of Climate Insurance Payouts Per Year



This figure shows the annual number of climate policy payouts made to CCRIF member countries over the 2008-2023 sample period.

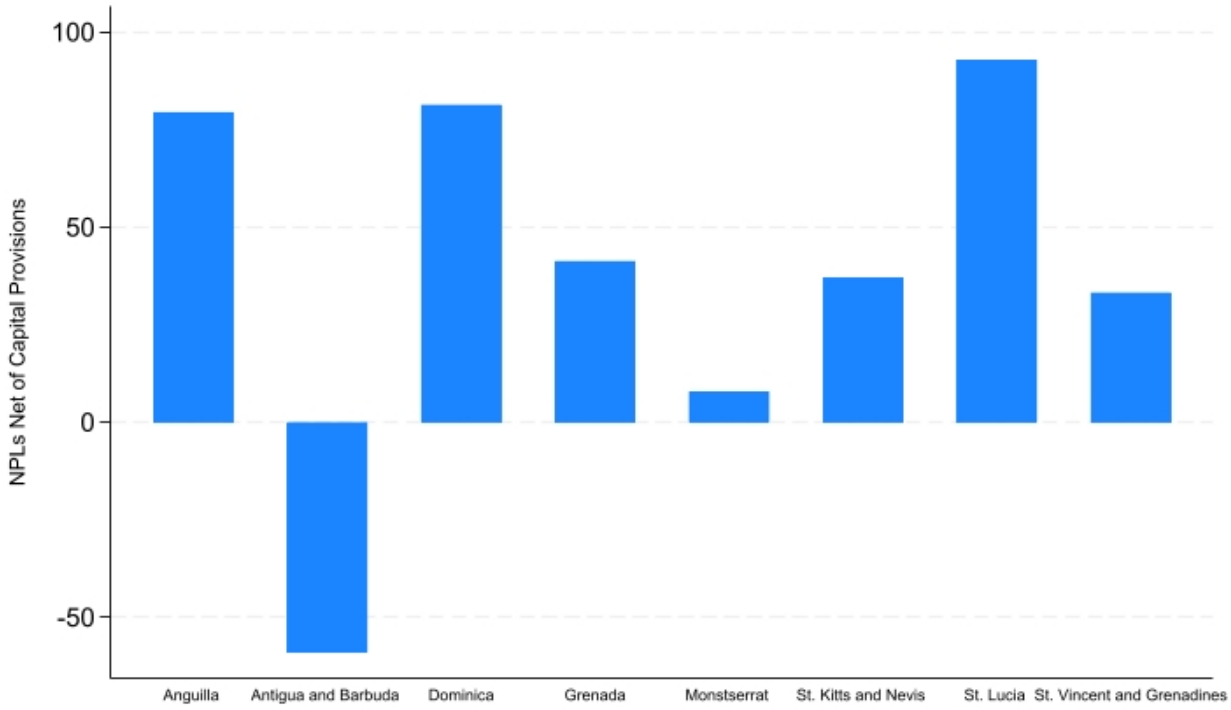
Figure A5: Value of Climate Insurance Payouts Per Year



This figure shows the annual value of climate policy payouts made to CCRIF member countries over the 2008-2023 sample period.

C.2 Cross Country Variation in NPLs Net of Capital Provisions

Figure A6: Distribution of NPLs Net of Capital Provisions



This figure shows the distribution of Non-Performing Loans (NPLs) net of capital provisions across the eight Eastern Caribbean Currency Union (ECCU) member states. The measure captures the extent to which banking sector exposures are covered by capital buffers, with higher values indicating weaker financial stability.

C.3 Impact of CCRIF Payouts on Government Expenditure

Table A1: Impact of CCRIF Payouts on Government Expenditure

	Capital Expenditure	Current Expenditure
	(1)	**(2)**
Treat * Post	51.519 **	-39.578 *
	(16.238)	(15.622)
Net Foreign Assets	0.020	0.035 **
	(0.015)	(0.012)
Broad Money Liabilities M2	-0.029 *	-0.051 **
	(0.012)	(0.009)
Claims on Private Sector	0.164 **	0.056 **
	(0.012)	(0.011)
Real Effective Exchange Rate	-3.443	-1.015
	(1.839)	(1.334)
Official Development Assistance	0.071	0.013
	(0.087)	(0.043)
Constant	215.153	212.408
	(175.912)	(115.355)
Year FE	Yes	Yes
N	528	528

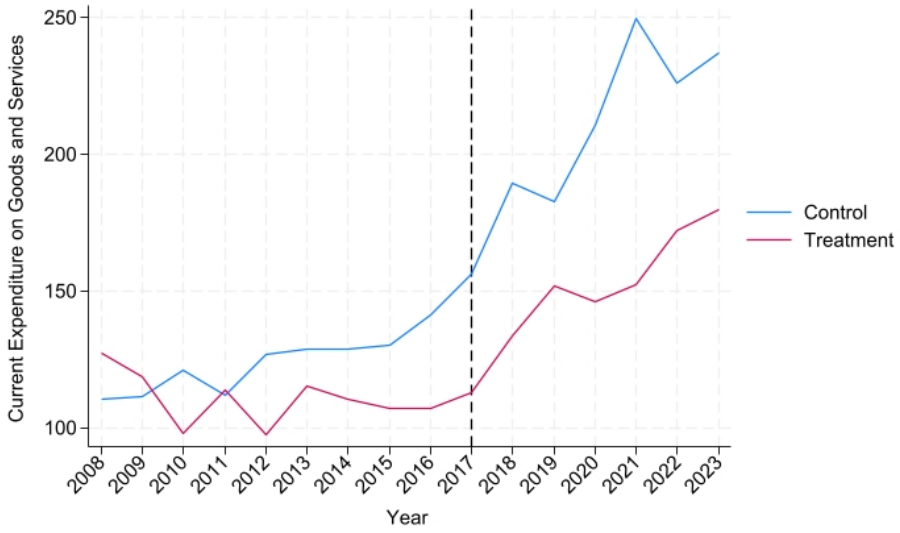
This table reports changes in government expenditure of ECCU countries in the aftermath of Cyclones Irma and Maria in 2017. The key independent variable, Treat x Post, compares government expenditure in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Column (1) shows results for the capital expenditure category of the fiscal accounts while column (2) shows results for the current expenditure category. Standard errors are double clustered at the country-year level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure A7: Parallel Trends for Capital Expenditure



This figure provides parallel trends for the single treatment DiD regression which compares the capital expenditure of countries which received a CCRIF insurance payout in 2017 to those which did not.Countries which received a CCRIF payment are assigned to the treated group (represented by red line) and countries which did not are assigned to the control group (represented by the blue line).

Figure A8: Parallel Trends for Current Expenditure



This figure provides parallel trends for the single treatment DiD regression which compares the current expenditure of countries which received a CCRIF insurance payout in 2017 to those which did not.Countries which received a CCRIF payment are assigned to the treated group (represented by red line) and countries which did not are assigned to the control group (represented by the blue line).

Figure A7 and Figure A8 shows parallel trend graphs for difference-in-differences regressions which compare the impact of CCRIF payouts on both capital and current expenditure in payout receiving countries to those which did not receive a payout following Cyclones Irma and Maria in 2017.

In Figure A7, which shows the results for capital expenditure, CCRIF payouts have a demonstrable impact on this particular category of government expenditure. This aligns with assumption of the theoretical model which argue that the liquidity provided by the payouts is intermediated by ECCU financial institutions through government expenditure on infrastructure repair and other long-term recovery spending which would be reported in the capital expenditure category of the fiscal accounts.

Figure A8, which shows the results for current expenditure on goods and services, indicates that while CCRIF payouts were also used to purchase non-durable items to assist with recovery efforts in the immediate aftermath of the cyclones, capital expenditure on infrastructure and other long-term recovery spending on capital goods was prioritized as current expenditure on goods and services remains significantly lower, throughout the entire post-payout period, in payout receiving countries when compared to countries which did not receive a payout.

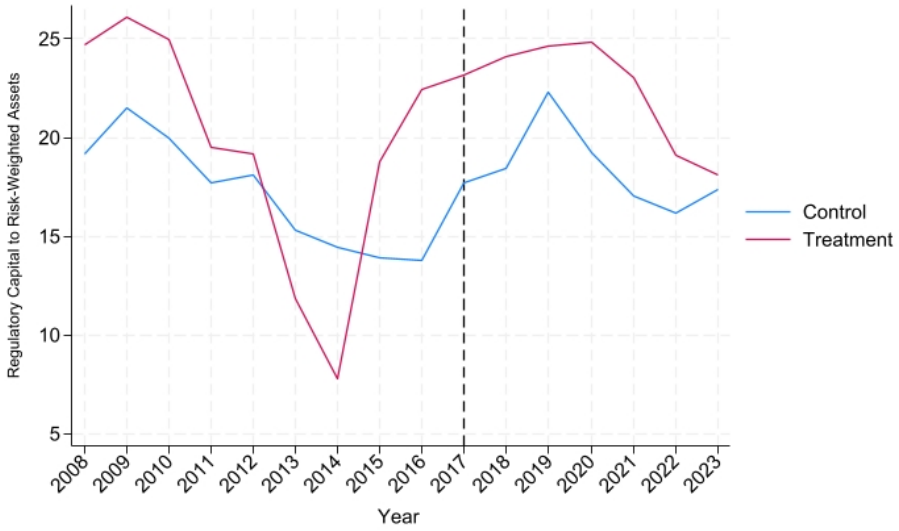
C.4 DiD Results for Solvency Indicators

Table A2: Impact of CCRIF Payouts on Regulatory Capital to Risk-Weighted Assets

	Regulatory Capital to Risk-Weighted Assets	
	(1)	**(2)**
Treat * Post	1.208	2.419
	(1.284)	(1.742)
Net Foreign Assets		-0.009 **
		(0.002)
Broad Money Liabilities M2		0.018 **
		(0.003)
Claims on Private Sector		-0.024 **
		(0.002)
Real Effective Exchange Rate		0.561 **
		(0.178)
Official Development Assistance		-0.004
		(0.011)
Constant	19.262 **	-27.371
	(0.522)	(18.237)
Adjusted R-squared	0.276	0.402
Year FE	Yes	Yes
Financial Institution (FI) FE	Yes	Yes
Disaster FE	No	Yes
FI x Country x ECCU x ECCB FE	No	Yes
N	528	528

This table reports changes in the regulatory capital to risk-weighted assets ratio of ECCU banks. The key independent variable, Treat x Post, compares the regulatory capital to risk-weighted assets ratio of banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Column (1) shows results with year and financial institution fixed effects and without controls while column (2) includes controls and all fixed effects. Standard errors are double clustered at the financial institution-year level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure A9: Parallel Trends for Regulatory Capital to Risk-Weighted Assets



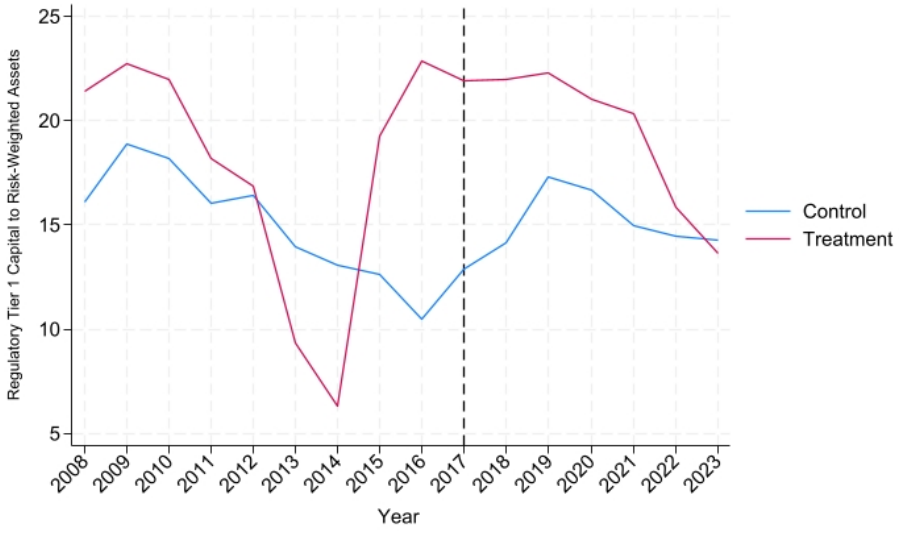
This figure provides parallel trends for the single treatment DiD regression which compares the regulatory capital to risk-weighted assets ratio of ECCU banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Banks in countries which received a CCRIF payment are assigned to the treated group (represented by red line) and banks in countries which did not are assigned to the control group (represented by the blue line).

Table A3: Impact of CCRIF Payouts on Regulatory Tier 1 Capital to Risk-Weighted Assets

	Regulatory T1 Capital to Risk-Weighted Assets	
	(1)	**(2)**
Treat * Post	0.661	1.186
	(1.267)	(1.761)
Net Foreign Assets		-0.009 **
		(0.002)
Broad Money Liabilities M2		0.019 **
		(0.003)
Claims on Private Sector		-0.021 **
		(0.002)
Real Effective Exchange Rate		0.552 **
		(0.176)
Official Development Assistance		0.001
		(0.011)
Constant	16.978 **	-35.346
	(0.515)	(18.481)
Adjusted R-squared	0.272	0.369
Year FE	Yes	Yes
Financial Institution (FI) FE	Yes	Yes
Disaster FE	No	Yes
FI x Country x ECCU x ECCB FE	No	Yes
N	528	528

This table reports changes in the regulatory T1 capital to risk-weighted assets ratio of ECCU banks. The key independent variable, Treat x Post, compares the regulatory T1 capital to risk-weighted assets ratio of banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Column (1) shows results with year and financial institution fixed effects and without controls while column (2) includes controls and all fixed effects. Standard errors are double clustered at the financial institution-year level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure A10: Parallel Trends for Regulatory Tier 1 Capital to Risk-Weighted Assets



This figure provides parallel trends for the single treatment DiD regression which compares the regulatory T1 capital to risk-weighted assets ratio of ECCU banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Banks in countries which received a CCRIF payment are assigned to the treated group (represented by red line) and banks in countries which did not are assigned to the control group (represented by the blue line).

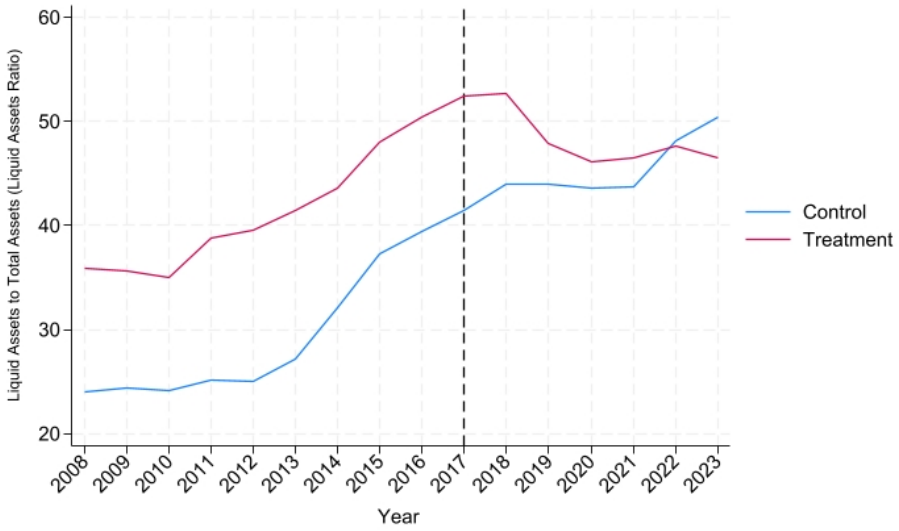
C.5 DiD Results for Liquidity Indicators

Table A4: Impact of CCRIF Payouts on Liquid Assets to Total Assets

	Liquid Assets to Total Assets	
	(1)	**(2)**
Treat * Post	-9.808 **	-3.084 **
	(0.853)	(0.981)
Net Foreign Assets		0.005 **
		(0.001)
Broad Money Liabilities M2		-0.001
		(0.002)
Claims on Private Sector		-0.008 **
		(0.001)
Real Effective Exchange Rate		-0.796 **
		(0.124)
Official Development Assistance		0.024 **
		(0.006)
Constant	43.174 **	130.550 **
	(0.255)	(12.495)
Adjusted R-squared	0.867	0.901
Year FE	Yes	Yes
Financial Institution (FI) FE	Yes	Yes
Disaster FE	No	Yes
FI x Country x ECCU x ECCB FE	No	Yes
N	528	528

This table reports changes in the liquid assets to total assets ratio of ECCU banks. The key independent variable, Treat x Post, compares the liquid assets to total assets ratio of banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Column (1) shows results with year and financial institution fixed effects and without controls while column (2) includes controls and all fixed effects. Standard errors are double clustered at the financial institution-year level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure A11: Parallel Trends for Liquid Assets to Total Assets



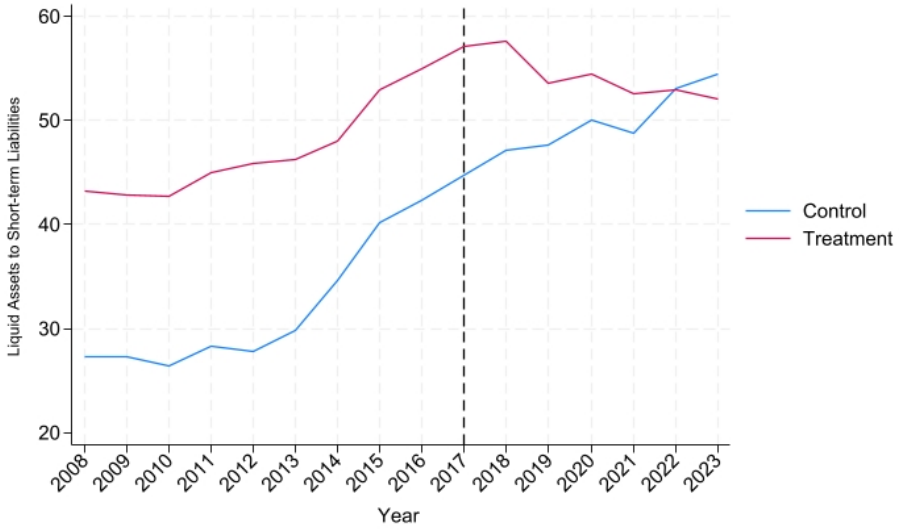
This figure provides parallel trends for the single treatment DiD regression which compares the liquid assets to total assets ratio of ECCU banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Banks in countries which received a CCRIF payment are assigned to the treated group (represented by red line) and banks in countries which did not are assigned to the control group (represented by the blue line).

Table A5: Impact of CCRIF Payouts on Liquid Assets to Short-term Liabilities

	Liquid Assets to Short-term Liabilities	
	(1)	**(2)**
Treat * Post	-11.362 **	-4.561 **
	(0.897)	(1.029)
Net Foreign Assets		0.006 **
		(0.001)
Broad Money Liabilities M2		-0.001
		(0.002)
Claims on Private Sector		-0.007 **
		(0.001)
Real Effective Exchange Rate		-0.700 **
		(0.121)
Official Development Assistance		0.024 **
		(0.006)
Constant	48.479 **	123.327 **
	(0.265)	(12.006)
Adjusted R-squared	0.882	0.908
Year FE	Yes	Yes
Financial Institution (FI) FE	Yes	Yes
Disaster FE	No	Yes
FI x Country x ECCU x ECCB FE	No	Yes
N	528	528

This table reports changes in the liquid assets to short-term liabilities ratio of ECCU banks. The key independent variable, Treat x Post, compares the liquid assets to short-term liabilities ratio of banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Column (1) shows results with year and financial institution fixed effects and without controls while column (2) includes controls and all fixed effects. Standard errors are double clustered at the financial institution-year level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure A12: Parallel Trends for Liquid Assets to Short-term Liabilities



This figure provides parallel trends for the single treatment DiD regression which compares the liquid assets to short-term liabilities ratio of ECCU banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Banks in countries which received a CCRIF payment are assigned to the treated group (represented by red line) and banks in countries which did not are assigned to the control group (represented by the blue line).

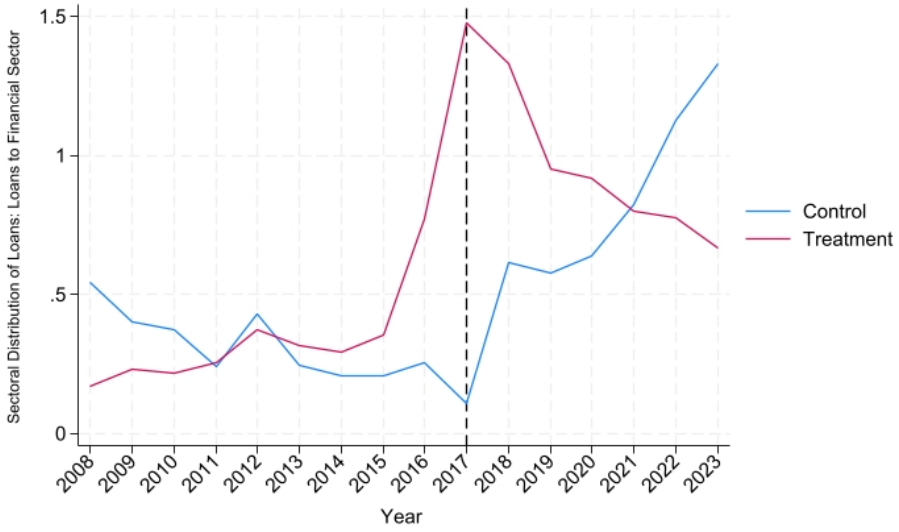
C.6 DiD Results for Sectoral Distribution of Loans

Table A6: Impact of CCRIF Payouts on Loans to Financial Sector

	Loans to Financial Sector	
	(1)	**(2)**
Treat * Post	-0.089	-0.139
	(0.115)	(0.172)
Net Foreign Assets		0.000
		(0.001)
Broad Money Liabilities M2		-0.001
		(0.001)
Claims on Private Sector		0.000
		(0.001)
Real Effective Exchange Rate		-0.014
		(0.016)
Official Development Assistance		-0.001
		(0.001)
Constant	0.595 **	2.54
	(0.042)	(1.356)
Adjusted R-squared	0.482	0.484
Year FE	Yes	Yes
Financial Institution (FI) FE	Yes	Yes
Disaster FE	No	Yes
FI x Country x ECCU x ECCB FE	No	Yes
N	528	528

This table reports changes in the distribution of loans to the financial sector. The key independent variable, Treat x Post, compares the loans to the financial sector issued by banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Column (1) shows results with year and financial institution fixed effects and without controls while column (2) includes controls and all fixed effects. Standard errors are double clustered at the financial institution-year level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure A13: Parallel Trends for Loans to Financial Sector



This figure provides parallel trends for the single treatment DiD regression which compares loans to the financial sector issued by ECCU banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not.Banks in countries which received a CCRIF payment are assigned to the treated group (represented by red line) and banks in countries which did not are assigned to the control group (represented by the blue line).

Table A7: Impact of CCRIF Payouts on Loans to Nonfinancial Sector

	Loans to Nonfinancial Sector	
	(1)	**(2)**
Treat * Post	6.202 **	3.115 **
	(1.083)	(1.045)
Net Foreign Assets		0.005 **
		(0.001)
Broad Money Liabilities M2		-0.007 **
		(0.002)
Claims on Private Sector		0.021 **
		(0.001)
Real Effective Exchange Rate		0.425 **
		(0.095)
Official Development Assistance		0.007
		(0.009)
Constant	30.922 **	-34.333 **
	(0.372)	(9.99)
Adjusted R-squared	0.782	0.871
Year FE	Yes	Yes
Financial Institution (FI) FE	Yes	Yes
Disaster FE	No	Yes
FI x Country x ECCU x ECCB FE	No	Yes
N	528	528

This table reports changes in the distribution of loans to the nonfinancial sector. The key independent variable, Treat x Post, compares the loans to the nonfinancial sector issued by banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Column (1) shows results with year and financial institution fixed effects and without controls while column (2) includes controls and all fixed effects. Standard errors are double clustered at the financial institution-year level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure A14: Parallel Trends for Loans to Nonfinancial Sector



This figure provides parallel trends for the single treatment DiD regressions which compares loans to the nonfinancial sector issued by ECCU banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not.Banks in countries which received a CCRIF payment are assigned to the treated group (represented by red line) and banks in countries which did not are assigned to the control group (represented by the blue line).

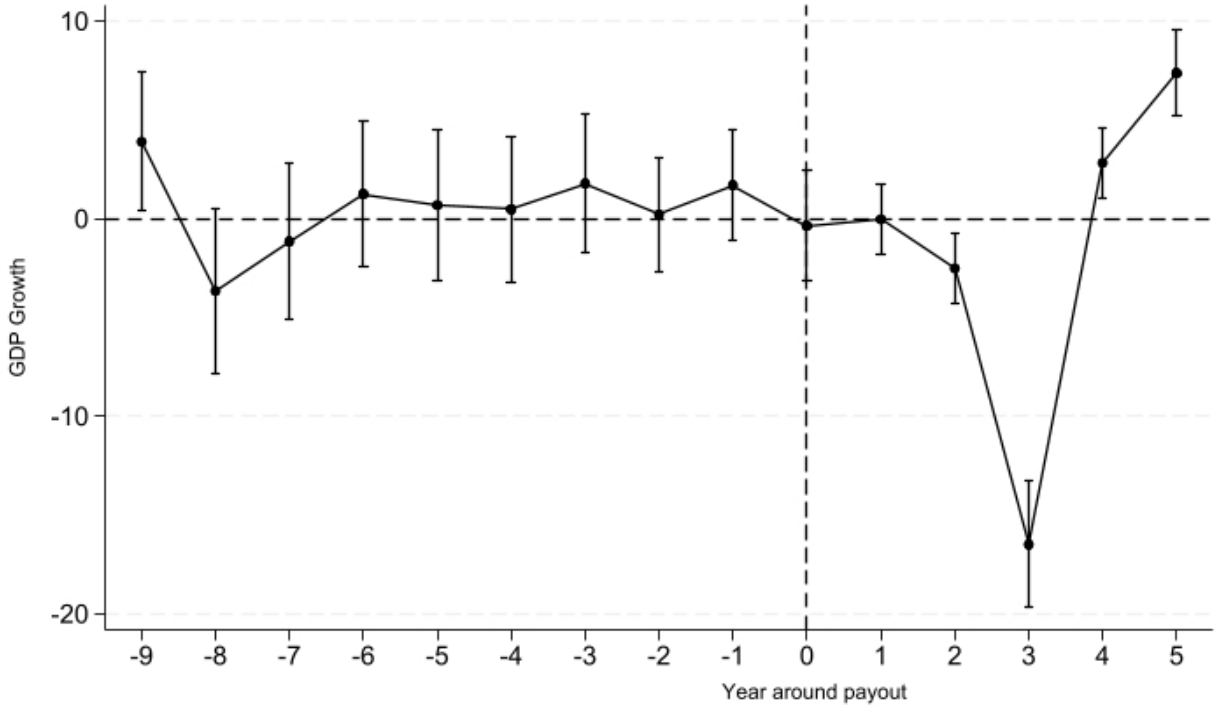
C.7 DiD Results for GDP Growth

Table A8: Impact of CCRIF Payouts on GDP Growth

	GDP Growth	
	(1)	**(2)**
Treat * Post	0.651	1.765
	(0.813)	(1.043)
Net Foreign Assets		-0.002 *
		(0.001)
Broad Money Liabilities M2		0.007 **
		(0.002)
Claims on Private Sector		-0.007 **
		(0.001)
Real Effective Exchange Rate		0.026
		(0.102)
Official Development Assistance		-0.001
		(0.005)
Constant	0.992 **	-2.373
	(0.272)	(11.461)
Adjusted R-squared	0.654	0.685
Year FE	Yes	Yes
Financial Institution (FI) FE	Yes	Yes
Disaster FE	No	Yes
FI x Country x ECCU x ECCB FE	No	Yes
N	528	528

This table reports changes in GDP growth. The key independent variable, Treat x Post, compares the GDP growth of countries which received a CCRIF insurance payout in 2017 to those which did not. Column (1) shows results with year and financial institution fixed effects and without controls while column (2) includes controls and all fixed effects. Standard errors are double clustered at the financial institution-year level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure A15: Effect of CCRIF Payouts on GDP Growth



This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the GDP growth of ECCU countries which received a payout. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

C.8 DiD Results for Profitability Indicators

Table A9: Impact of CCRIF Payouts on Interest Margin to Gross Income

	Interest Margin to Gross Income	
	(1)	**(2)**
Treat * Post	-1.390	-4.641 **
	(0.951)	(1.565)
Net Foreign Assets		-0.007 **
		(0.002)
Broad Money Liabilities M2		0.010 **
		(0.003)
Claims on Private Sector		-0.001
		(0.002)
Real Effective Exchange Rate		-0.006
		(0.162)
Official Development Assistance		-0.026 *
		(0.011)
Constant	61.975 **	45.515 **
	(0.311)	(14.186)
Adjusted R-squared	0.782	0.798
Year FE	Yes	Yes
Financial Institution (FI) FE	Yes	Yes
Disaster FE	No	Yes
FI x Country x ECCU x ECCB FE	No	Yes
N	528	528

This table reports changes in the interest margin to gross income ratio of ECCU banks. The key independent variable, Treat x Post, compares the interest margin to gross income ratio of banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Column (1) shows results with year and financial institution fixed effects and without controls while column (2) includes controls and all fixed effects. Standard errors are double clustered at the financial institution-year level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure A16: Parallel Trends for Interest Margin to Gross Income



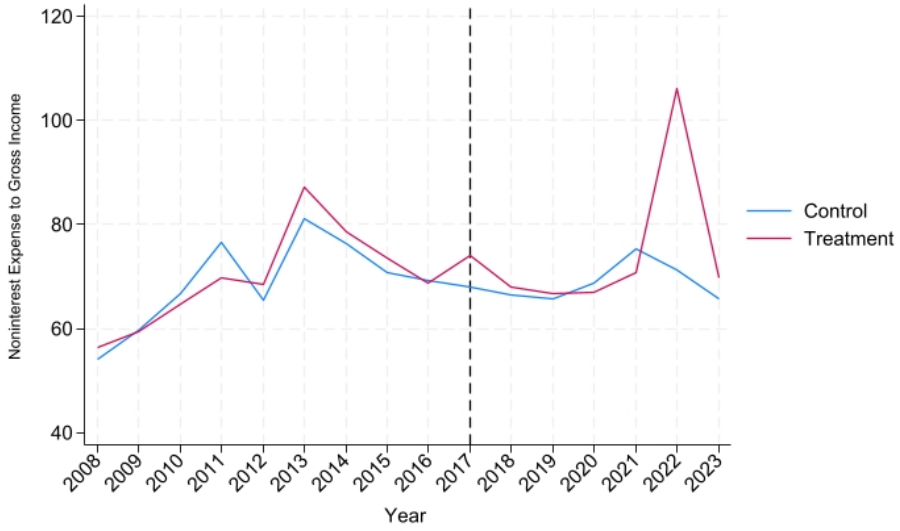
This figure provides parallel trends for the single treatment DiD regression which compares the interest margin to gross income ratio of ECCU banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not.Banks in countries which received a CCRIF payment are assigned to the treated group (represented by red line) and banks in countries which did not are assigned to the control group (represented by the blue line).

Table A10: Impact of CCRIF Payouts on Noninterest Expense to Gross Income

	Noninterest Expense to Gross Income	
	(1)	**(2)**
Treat * Post	4.651	4.121
	(2.545)	(4.298)
Net Foreign Assets		0.011 *
		(0.004)
Broad Money Liabilities M2		-0.016 *
		(0.006)
Claims on Private Sector		0.023 **
		(0.006)
Real Effective Exchange Rate		0.561
		(0.485)
Official Development Assistance		0.038
		(0.024)
Constant	69.576 **	3.098
	(0.738)	(43.924)
Adjusted R-squared	0.322	0.373
Year FE	Yes	Yes
Financial Institution (FI) FE	Yes	Yes
Disaster FE	No	Yes
FI x Country x ECCU x ECCB FE	No	Yes
N	528	528

This table reports changes in the noninterest expense to gross income ratio of ECCU banks. The key independent variable, Treat x Post, compares the noninterest expense to gross income ratio of banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not. Column (1) shows results with year and financial institution fixed effects and without controls while column (2) includes controls and all fixed effects. Standard errors are double clustered at the financial institution-year level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

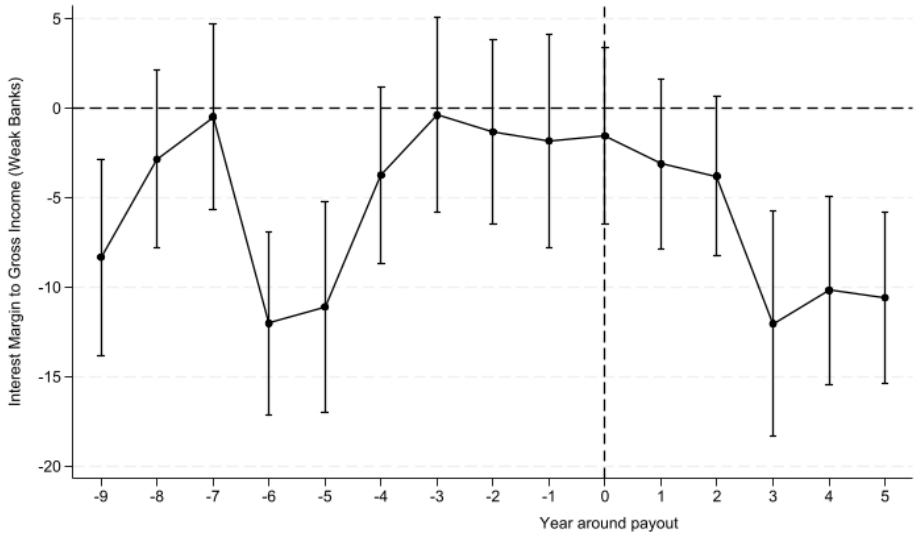
Figure A17: Parallel Trends for Noninterest Expense to Gross Income



This figure provides parallel trends for the single treatment DiD regressions which compare the noninterest expense to gross income ratio of ECCU banks in countries which received a CCRIF insurance payout in 2017 to those in countries which did not.Banks in countries which received a CCRIF payment are assigned to the treated group (represented by red line) and banks in countries which did not are assigned to the control group (represented by the blue line).

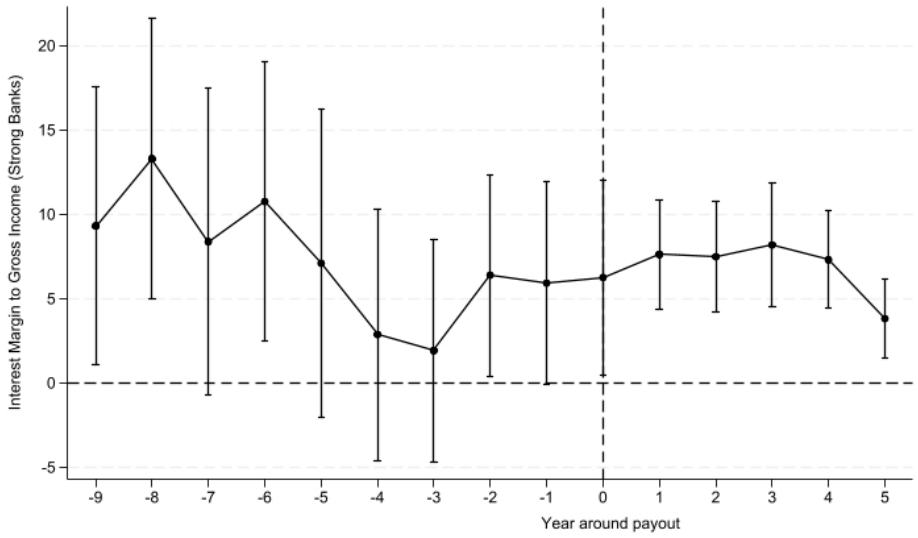
C.9 Empirical Test of Bad Luck Hypothesis Heterogeneity by Asset Quality

Figure A18: Effect of CCRIF Payouts on Interest Margin to Gross Income of Weak Banks



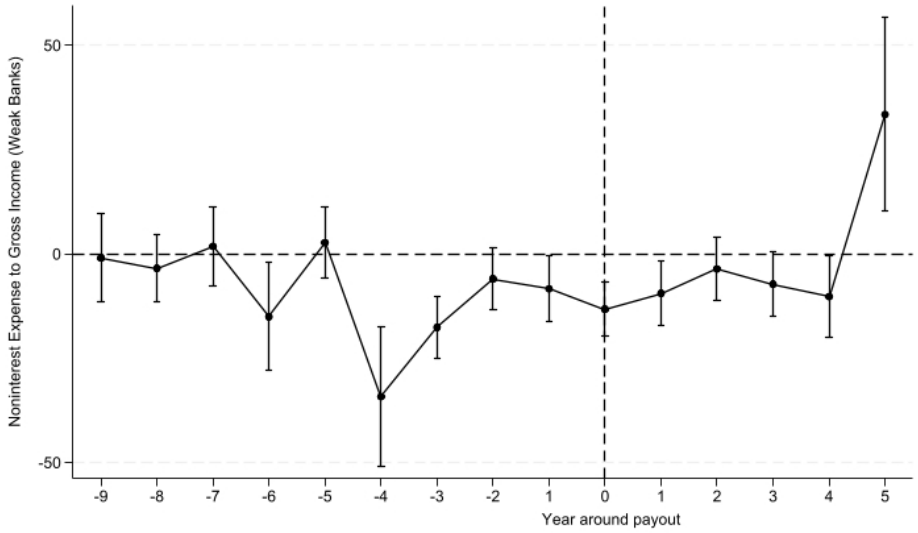
This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the interest margin to gross income ratio of weak ECCU banks in countries which received a payout. Weak banks are defined as those with NPLs above the median before the payouts were issued in 2017. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A19: Effect of CCRIF Payouts on Interest Margin to Gross Income of Strong Banks



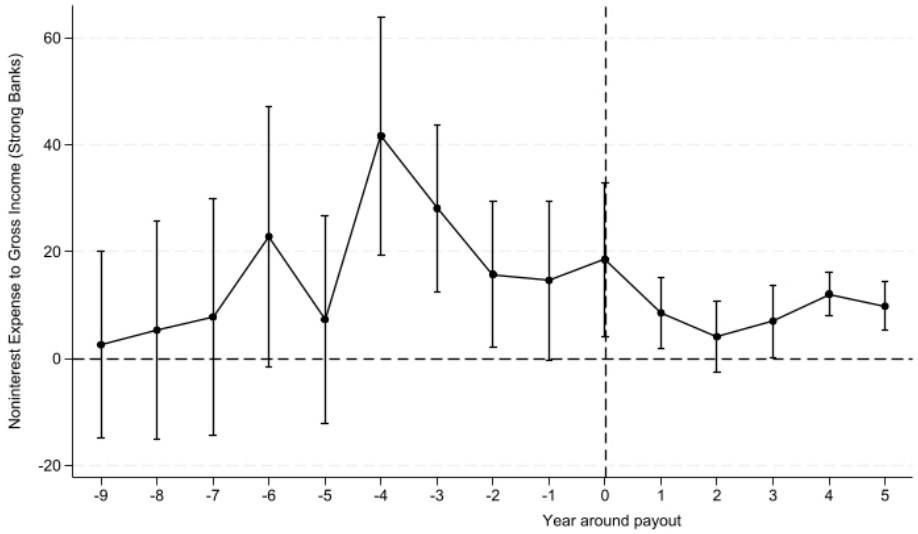
This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the interest margin to gross income ratio of strong ECCU banks in countries which received a payout. Strong banks are defined as those with NPLs below the median before the payouts were issued in 2017. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A20: Effect of CCRIF Payouts on Noninterest Expense to Gross Income of Weak Banks



This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the noninterest expense to gross income ratio of weak ECCU banks in countries which received a payout. Weak banks are defined as those with NPLs above the median before the payouts were issued in 2017. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

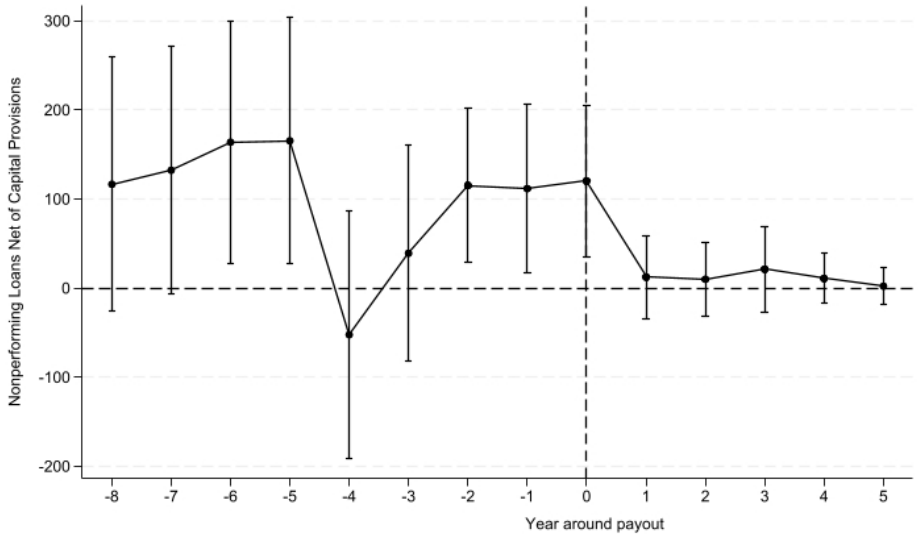
Figure A21: Effect of CCRIF Payouts on Noninterest Expense to Gross Income of Strong Banks



This figure shows estimates of equation (2), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the noninterest expense to gross income ratio of strong ECCU banks in countries which received a payout. Strong banks are defined as those with NPLs below the median before the payouts were issued in 2017. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

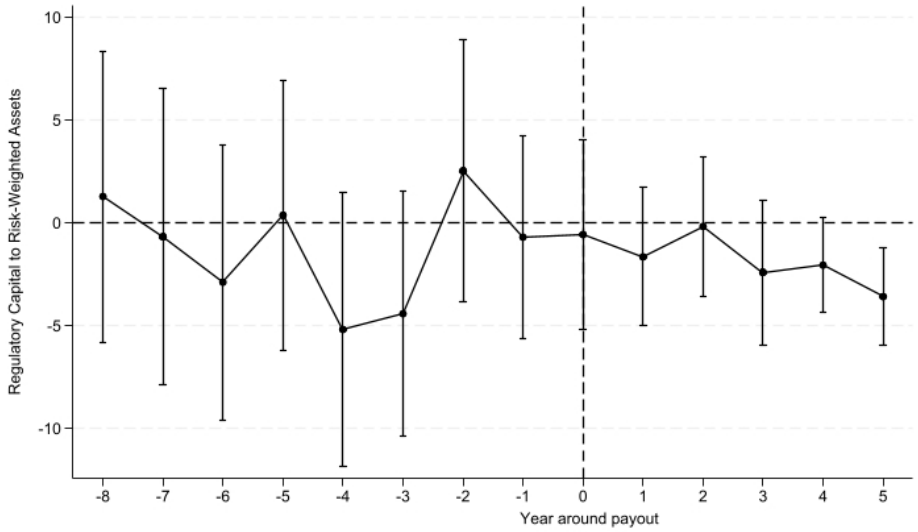
D. Results with Lagged Dependent Variables

Figure A22: Effect of CCRIF Payouts on Nonperforming Loans Net of Capital Provisions (Lagged)



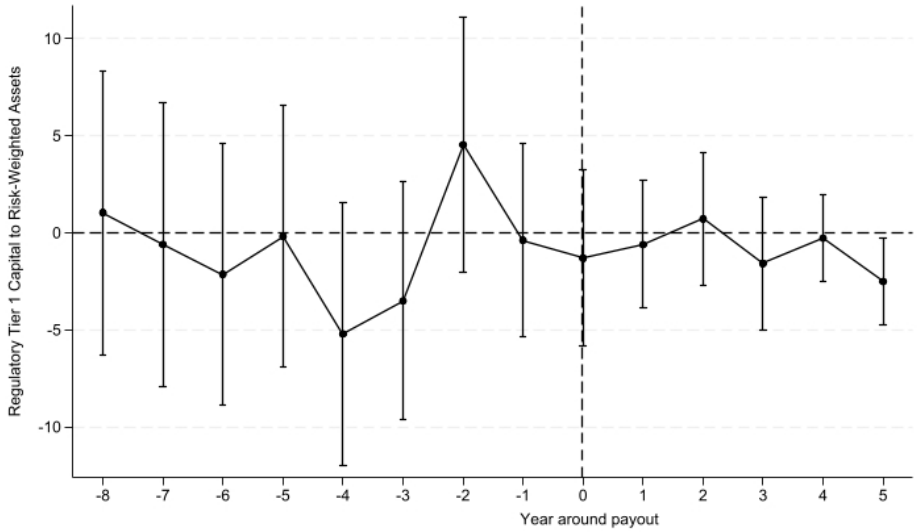
This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the nonperforming loans net of capital provisions ratio of ECCU banks in countries which received a payout. The lagged nonperforming loans net of capital provisions ratio is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A23: Effect of CCRIF Payouts on Regulatory Capital to Risk-Weighted Assets (Lagged)



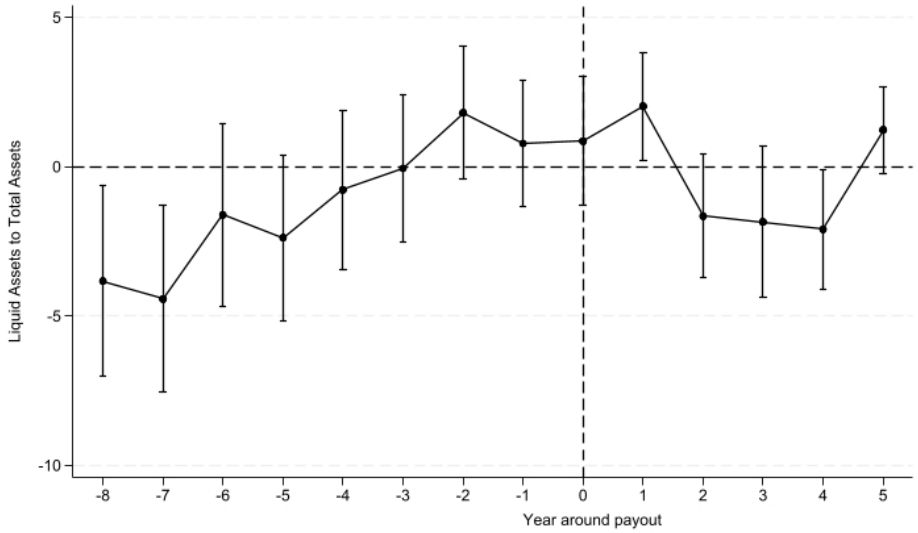
This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the regulatory capital to risk-weighted assets ratio of ECCU banks in countries which received a payout. The lagged regulatory capital to risk-weighted assets ratio is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A24: Effect of CCRIF Payouts on Regulatory Tier 1 Capital to Risk-Weighted Assets (Lagged)



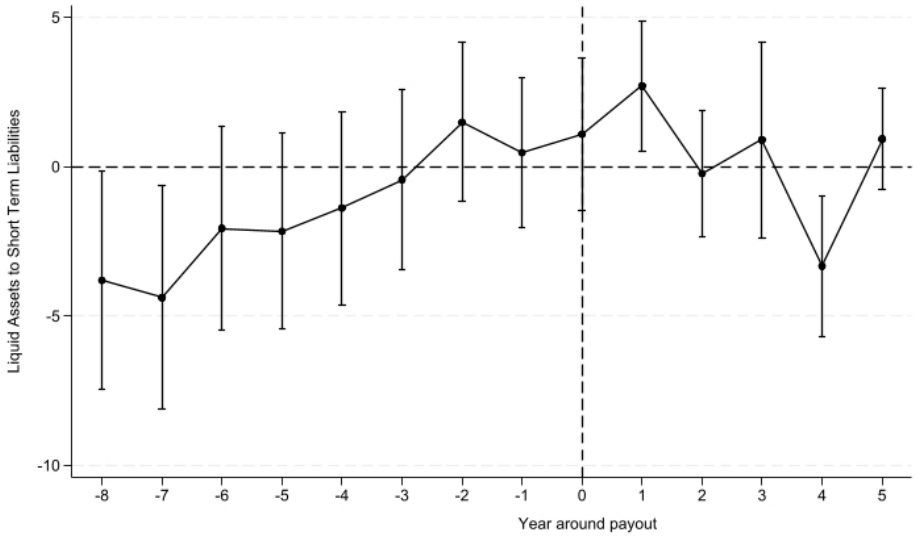
This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the regulatory tier 1 capital to risk-weighted assets ratio of ECCU banks in countries which received a payout. The lagged regulatory tier 1 capital to risk-weighted assets ratio is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A25: Effect of CCRIF Payouts on Liquid Assets to Total Assets (Lagged)



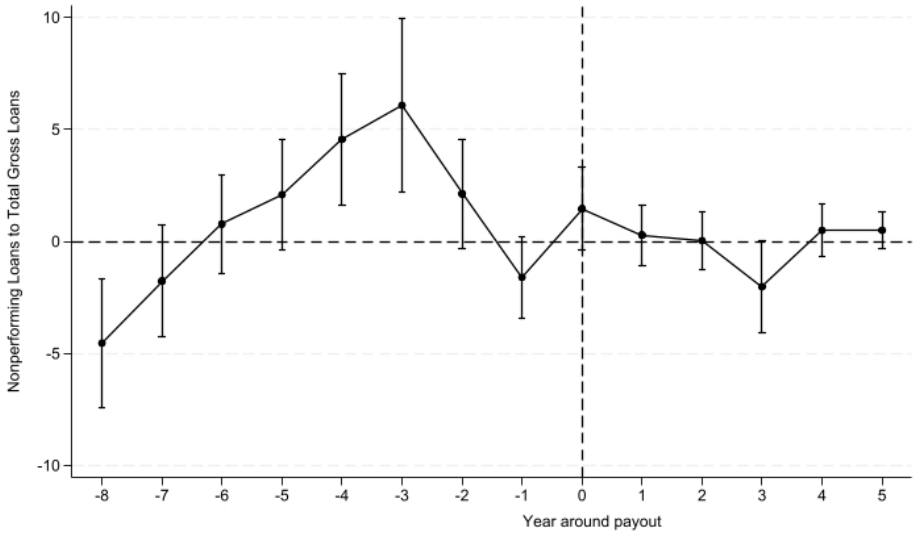
This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the liquid assets to total assets ratio of ECCU banks in countries which received a payout. The lagged liquid assets to total assets ratio is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A26: Effect of CCRIF Payouts on Liquid Assets to Short Term Liabilities (Lagged)



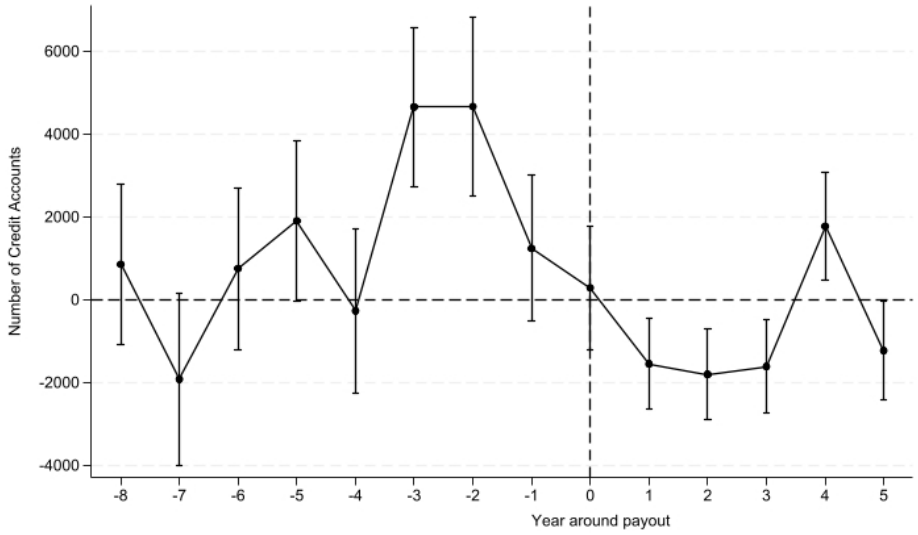
This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the liquid assets to short-term liabilities ratio of ECCU banks in countries which received a payout. The lagged liquid assets to short-term liabilities ratio is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A27: Effect of CCRIF Payouts on Nonperforming Loans to Total Gross Loans (Lagged)



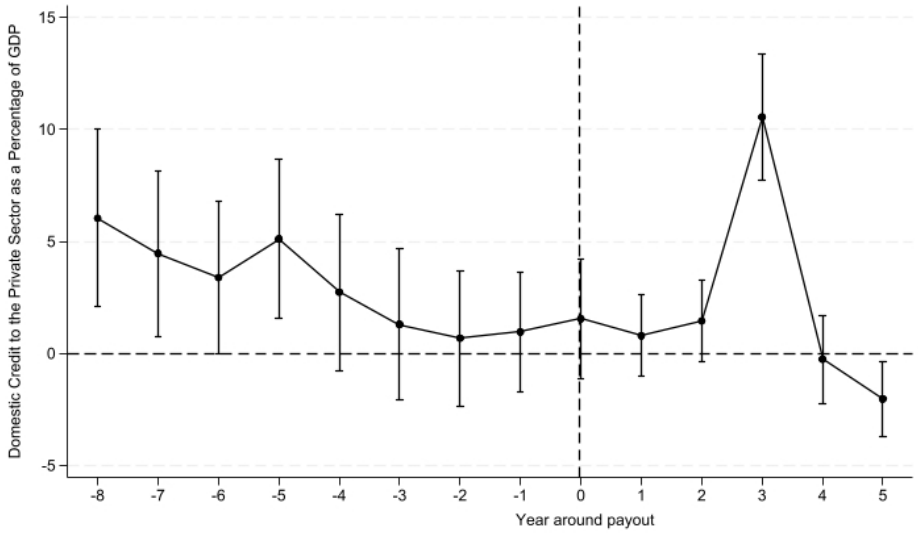
This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the nonperforming loans to total gross loans ratio of ECCU banks in countries which received a payout. The lagged nonperforming loans to total gross loans ratio is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A28: Effect of CCRIF Payouts on Number of Credit Accounts (Lagged)



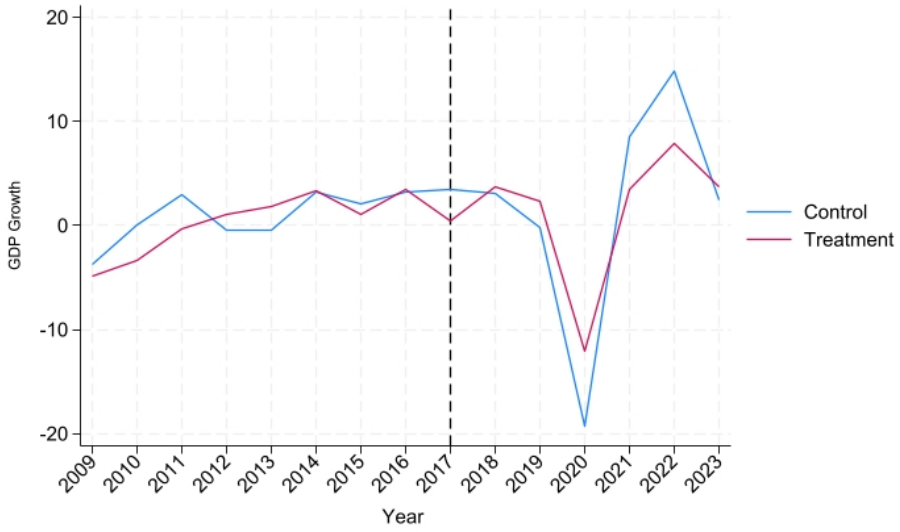
This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the number of credit accounts of ECCU banks in countries which received a payout. The lagged number of credit accounts is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A29: Effect of CCRIF Payouts on Domestic Credit to the Private Sector as a Percentage of GDP (Lagged)



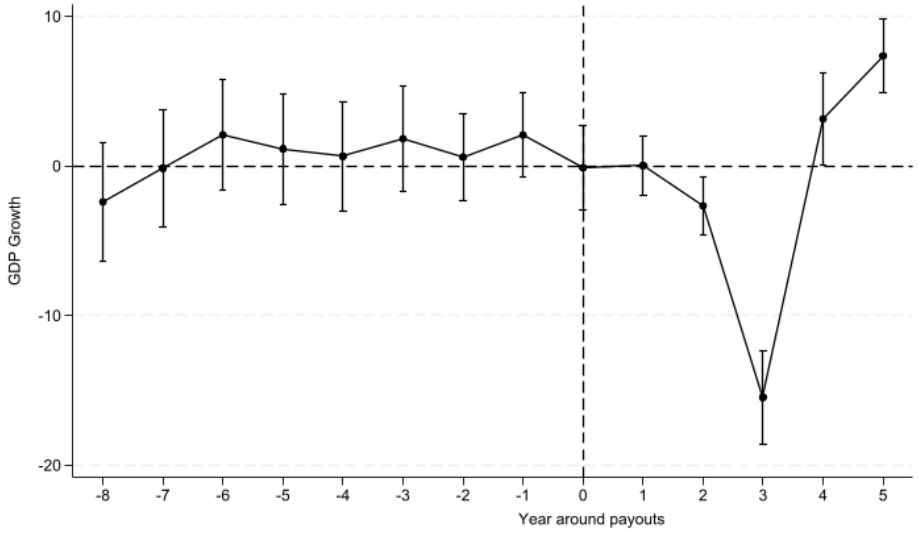
This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the domestic credit to the private sector as a percentage of GDP for countries which received a payout. The lagged domestic credit to the private sector as a percentage of GDP is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A30: Parallel Trends for GDP Growth (Lagged)



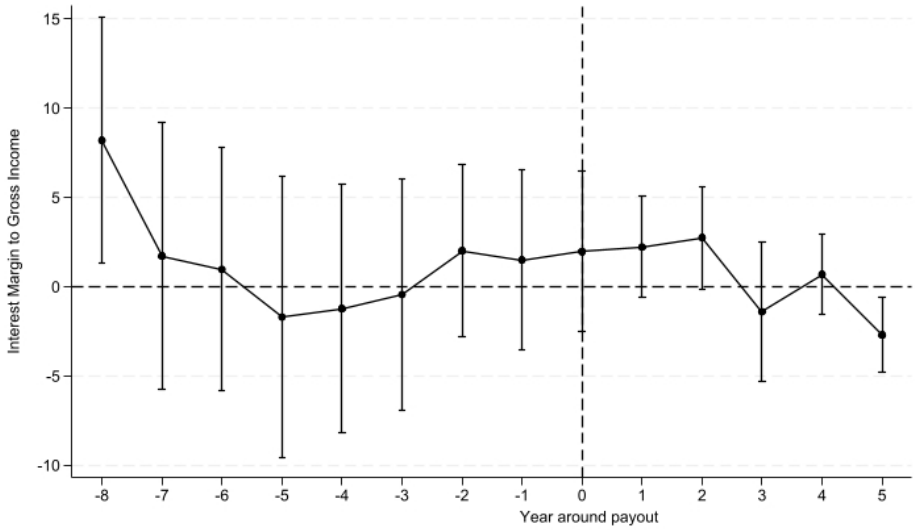
This figure presents the parallel trends constructed from regressions which include as a regressor the lagged dependent variable for GDP growth in a DiD regression which compares the GDP growth of countries which received a CCRIF insurance payout in 2017 to those in countries which did not.

Figure A31: Effect of CCRIF Payouts on GDP Growth (Lagged)



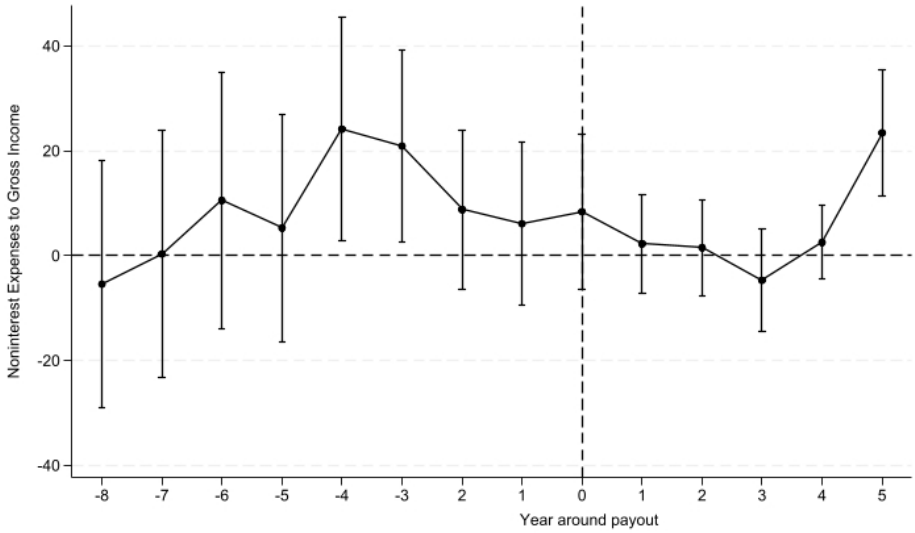
This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the GDP growth for countries which received a payout. The lagged GDP growth is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A32: Effect of CCRIF Payouts on Interest Margin to Gross Income (Lagged)



This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the interest margin to gross income ratio of ECCU banks in countries which received a payout. The lagged interest margin to gross income ratio is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.

Figure A33: Effect of CCRIF Payouts on Noninterest Expense to Gross Income (Lagged)



This figure shows estimates of equation (3), describing the effect of CCRIF insurance payouts following the significant damage caused by Cyclones Irma and Maria in 2017 among islands within the Eastern Caribbean. In this case, the dependent variable is the noninterest expense to gross income ratio of ECCU banks in countries which received a payout. The lagged noninterest expense to gross income ratio is included as a regressor. The regression includes year fixed effects, disaster fixed effects and financial institution-country-ECCU-ECCB fixed effects. The figure includes 95% confidence intervals.