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Impact of tropical storms on the banking sector in the British Colonial Caribbean

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Abstract

This paper investigates the impact of four historical tropical storms on the Colonial Bank's operations in the British Caribbean between 1922 and 1927. By employing a high-frequency data set of bank transactions, this study reveals how these severe shocks influenced the banking activities of clients. The findings reveal a multifaceted and significant impact of tropical storm strikes on the banks' operations, particularly a surge in borrowing via overdrafts of current accounts. Moreover, the study reveals the multifaceted nature of such storms' impact on the bank's functionality, with affected branches demonstrating an uptick in deposits and savings as a strategy to mitigate funding shocks. The results of the econometric analysis indicate that the impact of such storms on banks' functionality during the early 20th century was significant and multidimensional. It highlights the critical role that the Colonial Bank plays in facilitating recovery from these devastating events and contributes to the existing literature by studying multiple shocks at different geographical locations and time frames.

Keywords Environmental economic history · Banking history · Financial response to disasters · Caribbean economic development · Early 20th century banking · Natural disasters

JEL Classification Q54 · N26 · G21 · O16 · G01

1 Introduction

Historically, the Caribbean economy has been significantly impacted by natural disasters, most notably tropical storms, which have caused widespread damage in various sectors. Among the sectors most affected, the decrease in crop exports (Mohan and Strobl 2013; Mohan 2017; Mohan and Strobl 2017), the destruction of

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structural assets (Smith 2012; Mulcahy 2008), and the degradation of infrastructure (Lugo 2000; Rasmussen 2004) stand out, which have had far-reaching implications on the financial system. In the case of Colonial Jamaican sugar estates, Huesler and Strobl (2023) show that hurricane strikes reduced the amount of sugar produced and destroyed machinery on the estates. In turn, estate owners needed money to either repair or buy new and more advanced machinery (Huesler and Strobl 2023). During the period in question, Jamaica seemingly lacked a formalized strategy for post-disaster management. The prevailing British colonial approach to disaster response emphasized maintaining colonial dominance and fiscal conservatism, leading to a reliance on philanthropy for financial assistance rather than direct intervention by the imperial government (Webber 2018). Similarly, the local authorities did not offer any specific support in the aftermath of natural disasters. Instead, limited aid was available through existing local programs for poverty relief, assisting those who fell into destitution following a hurricane (Bryan 2000). Consequently, the responsibility for post-disaster recovery largely fell to private efforts, as the government's assistance was minimal.

In the context of the Caribbean, the financial system was in a nascent stage until the advent of the 19th century. This era marked the establishment of the Colonial Bank in 1836, which ushered in a new phase of financial development (Brown 1990). The establishment of the Colonial Bank was driven by the need to provide the financial necessities of the agricultural industry and to facilitate trade within the Caribbean (Hudson 2014; Monteith 2003). The bank offered services that accepted savings and deposits, but its role in providing long-term investment capital was limited due to prohibitions on lending against property (Hudson 2014; Monteith 2003; Lobdell 1972). The reason why the Colonial Bank could not lend money against property was that its charter specified that it was a commercial bank, focusing only on short-term financing of agriculture and trade, not long-term financing (Lobdell 1972; Monteith 2003).

During this period, Caribbean colonies were largely agriculturally driven economies, although with varying degrees of dependence (Bulmer-Thomas 2012). The Colonial Bank successfully fulfilled the role of financial intermediary for its clients in trade and agricultural businesses in the British Caribbean and became the dominant force in the British West Indian financial sector. The Colonial Bank's market position was further bolstered following the sugar price collapse in 1920. This financial shock led to a number of U.S. banks shuttering their Caribbean branches, while maintaining a primary focus on Cuba, leaving the Colonial Bank with a larger share of the market (Quigley 1989).

This paper analyses the influence of four historic tropical cyclones on the banking operations of the British West Indies, with a particular focus on the Colonial Bank during the period from 1922 to 1927, acknowledging the institution's significant role in the region's economy. In September 1922, the first of these storms unleashed winds of 90 to 140 km/h, predominantly afflicting the islands of Antigua, Dominica, and St. Kitts. The devastation was not isolated, as a subsequent tempest in 1924, boasting winds that exceeded 133 km/h, extended its impact to include St. Lucia alongside the previously affected islands. The severity of the damages from these events was starkly articulated by the Governor of Antigua, who reported: *"[...]*

Antigua, 3 killed; estimated damage, £7,500. [...] The estimated damage to private property in St. Kitts is about £60,500 and £8,000 to Public Works." The Jamaica Gleaner (1924a). Two years thereafter, the islands endured additional meteorological adversities with two more storms in 1926, notably the *Nassau Hurricane* and the *Great Miami Hurricane*, which, despite their reduced wind speeds of 66 to 83 km/h, inflicted significant destruction in the Bahamas and Florida, as well as revisiting the earlier mentioned Caribbean islands.

In assessing the impact of these tropical storms on the clientele of the Colonial Bank, I used high-frequency banking data from 26 geolocated branches. The data, reflecting balances of savings and current accounts, deposits, and the extent of overdrawn accounts, is evaluated semi-monthly at the branch level. This paper intertwines these financial records with storm tracks affecting the Colonial Bank's branches. To this end, I combined the storm tracks with a wind field model to estimate their wind speed at the Colonial Bank branches. By transforming these wind speeds, I derived a proxy for the potential destruction at the exact location of the given branches. The granularity of this high-frequency data is used to shed light on the temporal and spatial variations of the storms' impact on the financial activity of customers in Colonial Bank's network. The findings of this paper reveal a noticeable disruption in banking operations, evidenced by a spike in borrowing via overdrafts of current accounts following storm strikes. Furthermore, the analysis discloses a complex pattern of response to the storms, with the data indicating an increase in deposits and savings at the affected branches, suggesting a strategic approach to mitigate funding shocks.

This paper contributes to the existing literature in several important ways. First, it serves as a unique historical case study, providing an extensive analysis of the early 20th century British West Indies, when the financial system was nascent. As such, it provides information on an era often overlooked compared to contemporary historical case studies or those focussing on singular national entities.[1] This expands our understanding of how clients of financial institutions responded during the late modern era. In particular, the study examines not one but four independent storms, each with varying degrees of impact on different branches. This approach contrasts with case studies centered on a single event (see e.g. Schüwer et al. 2019; Mercantini 2002). Second, the paper uses a unique high-frequency data set of banking variables, which distinguishes it from previous research relying on methods such as questionnaires (Sawada and Shimizutani 2008), yearly tax returns (Deryugina et al. 2014), or lower-frequency banking data sets (see e.g. Cortés and Strahan 2017; Brei et al. 2019; Bayangos et al. 2021; Koetter et al. 2020). This aids in tracing the temporal evolution of the storm's impact and sheds further light on client responses to such shocks. Third, the analysis explores the consequences of hurricane strikes in a context where long-term borrowing was markedly constrained by the nascent financial infrastructure. This unique angle sheds light on aspects of hurricane effects that are

[1] See e.g. Bayangos et al. (2021), Wu et al. (2022), and Brei et al. (2019) exploring the aftermath of natural disasters in the 21st century, while Okazaki et al. (2023) examines the impact of the Great Kanto Earthquake during a similar period but restricts its focus to a single event at one geographical location.

often overlooked in favor of loan-focused analyses in the prevailing literature.[2] By examining the broader financial repercussions on bank clients, this paper provides a more comprehensive understanding of the economic impact of natural disasters in historical contexts.[3] Finally, this paper explores the impact of tropical storms on several banking variables, allowing a differentiated conclusion on how clients reacted to tropical storms.

The remainder of this paper is organized as follows. Section 2 provides a historical background, followed by the data sources. Section 4 presents the methodology, followed by the econometric analysis in Sect. 5. Finally, Sect. 6 briefly concludes.

2 Historical background

2.1 History of the Colonial Bank

Before the formal establishment of banking institutions, the plantation system in the Caribbean was financed primarily by capital from merchants who lent money to local planters (Brown 1990; Bowen 1939). However, with the abolition of slavery in 1838, the increased cost of sugar production necessitated greater capital investment for efficiency improvements (Cumper 1954; Beachey 1957). The Colonial Bank's inception in 1836 marked a pivotal shift in the Caribbean's financial landscape. Following the *Bank Charter Act of 1833*, the bank's charter signified the era's burgeoning financial developments (Brown 1990). As a primary financier of agriculture and trade, the Colonial Bank played a central role in the Caribbean's economic growth (Hudson 2014; Monteith 2003). However, since the Colonial Bank was prohibited from lending against real estate or other properties from 1858 onwards, it was effectively unable to provide long-term investment capital (Monteith 2003; Lobdell 1972). Therefore, the Colonial Bank primarily focused on providing clients with the facilities to save and invest their money, as well as granting short-term advances. The bank's operations were initially limited to the British Caribbean colonies, but gradually expanded its reach to other regions in the world (Monteith 2003). At the same time, the first savings banks were established, allowing the general population of the Caribbean to save money (Hudson 2014). The first savings banks were established in Jamaica and Guyana, followed by many other islands later in the 19th century (Hudson 2014). However, these banks were only for smaller clients. Until

[2] Typical foci include Hurricane Katrina (Gallagher and Hartley 2017; Deryugina et al. 2014), earthquakes in China from 2009–2017 (Wu et al. 2022), the 1995 Kobe earthquake (Sawada and Shimizutani 2008), various Caribbean hurricanes (Brei et al. 2019), and the 2004 Indian Ocean Tsunami (Nguyen and Wilson 2020).

[3] When analysing the impact of tropical storms, it is important to consider other natural disasters that may have an impact, such as earthquakes and tsunamis. However, earthquakes and tsunamis are considerably rarer and tend to cause more localized damage. In their study, O'loughlin and Lander (2003) compiled an extensive list of all earthquakes and tsunamis that occurred in the Caribbean between 1498 and 1998. From 1922 to 1927, there were no earthquakes in the Caribbean basin, except for one tsunami that only impacted Galveston, a location where Colonial Bank did not have a branch. Therefore, Colonial Bank's customers were not affected by any other natural disasters.

the end of the 19th century, when the Royal Bank of Canada entered the Caribbean banking sector, the Colonial Bank was the dominant force in the Caribbean and held a monopoly in almost all Caribbean colonies (Monteith 2003; Lobdell 1972).[4] However, primary Canadian banks sought to increase their power in the domestic market through mergers, rather than expanding their influence in the Caribbean (Quigley 1989).

In the late 19th century, the beetroot sugar crisis had a detrimental effect on the performance of the Colonial Bank, as evidenced by a decrease in net profits greater than 50% between 1877 and 1906 and a ten-fold increase in bad debts (Wai 2010).[5] The severe decline in sugar prices in the 1920s not only had a significant impact on the performance of the Colonial Bank in the West Indies, but also on banks operating in the United States (Quigley 1989). These institutions faced significant financial losses, and as a result, several US banks closed their branches in the Caribbean region (Quigley 1989). During the 1920s, the Colonial Bank's market share, which was determined by the currency issued, was approximately equal to the combined market share of all Canadian banks operating in the Caribbean (Ryan 2019). In 1925, the Colonial Bank became a global bank and changed its name to Barclays Bank (Dominion, Colonial and Overseas). The new bank was formed through the amalgamation of Colonial Bank, Barclays, the Anglo-Egyptian Bank and the National Bank of South Africa (Monteith 2003; Crossley and Blandford 1975).

2.2 British Colonial Caribbean economies

At the beginning of the 20th century most Caribbean islands still relied on agricultural industries and commodities (Bulmer-Thomas 2012). One of the most important crops was sugar, which still represented approximately 70% of Caribbean exports between 1922 and 1927, underscoring the region's significant dependence on the sugar industry (Bulmer-Thomas 2012). However, these economies also relied on other crops and commodities. As the British Navy transitioned from coal to oil, demand for oil increased, oil production in Trinidad increased, so that the share of petroleum and petroleum products exported from Trinidad increased from not even 5% in 1915 to almost 50% in 1930 (Mulchansingh 1971). Furthermore, Britain and Commission (1945) reported the extraction of bauxite (the primary ore of aluminium), diamonds, and gold in British Guiana, although mineral resources were scarce on other islands. Bulmer-Thomas (2012) argued that the colonies' overreliance on

[4] Prior to World War I, U.S. banks were prohibited from conducting business outside of the United States (Monteith 2003; Quigley 1989). Following the First World War, the *National City Bank* entered the Caribbean market. Given its close ties with U.S. firms, it emerged as a formidable competitor, particularly in Haiti (Hudson 2013). However, Canadian banks did not feel threatened as the National City Bank's inexperience with branch banking was seen as a big disadvantage (Quigley 1989).

[5] It is important to mention that the Colonial Bank was always closely tied to sugar. Monteith (1997) estimates that between 1926 and 1939 the clients of the Colonial Bank were responsible for 80% of the sugar in the West Indies.

Table 1 Economic structure

Country	Year	Sugar	Rum	Cacao	Bananas	Oils	Gold	Total Exports
Antigua	1922	0.97	0.00	0.00	0.00	0.00	0.00	813,512.00
Barbados	1922	0.55	0.00	0.00	0.00	0.00	0.00	4,041,108.00
Dominica	1922	0.00	0.00	0.14	0.00	0.00	0.00	329,698.00
Grenada	1922	0.00	0.00	0.68	0.00	0.00	0.00	1,081,278.00
Guyana	1922	0.55	0.01	0.00	0.00	0.00	0.01	11,695,033.00
Jamaica	1922	0.24	0.02	0.04	0.48	0.00	0.00	16,599,194.00
St.Kitts	1922	0.89	0.00	0.00	0.00	0.00	0.00	691,085.00
St.Lucia	1922	0.62	0.00	0.25	0.01	0.00	0.00	484,226.00
St.Vincent	1922	0.10	0.00	0.15	0.00	0.00	0.00	58,326.00
Trinidad & Tobago	1922	0.33	0.00	0.34	0.00	0.22	0.00	15,482,508.00
Antigua	1927	0.98	0.00	0.00	0.00	0.00	0.00	1,798,807.00
Barbados	1927	0.66	0.00	0.00	0.00	0.00	0.00	6,052,231.00
Dominica	1927	0.00	0.00	0.30	0.00	0.00	0.00	300,114.00
Grenada	1927	0.00	0.00	0.65	0.00	0.00	0.00	2,277,285.00
Guyana	1927	0.57	0.03	0.00	0.00	0.00	0.01	15,506,812.00
Jamaica	1927	0.18	0.02	0.04	0.54	0.00	0.00	21,165,300.00
St.Kitts	1927	0.98	0.00	0.00	0.00	0.00	0.00	1,223,493.00
St.Lucia	1927	0.56	0.00	0.23	0.02	0.00	0.00	659,580.00
St.Vincent	1927	0.35	0.00	0.12	0.00	0.00	0.00	95,611.00
Trinidad & Tobago	1927	0.15	0.00	0.33	0.00	0.40	0.00	24,281,007.00

This Table illustrates the share of the major export products relative to the value of total exports. The underlying data is from (Bulmer-Thomas 2012)

the export of one or two products presented significant challenges.[6] On a broader scale, the West Indies lacked a manufacturing industry, resulting in a high dependence on imports for manufactured goods such as clothing from the United States and Great Britain (Britain and Commission 1945).

Table 1 shows the share of the main export products relative to the value of total exports per colony. The data are obtained from Bulmer-Thomas (2012). Although all economies in Table 1 obtain their exports from the primary sector, there exists a vast heterogeneity with respect to the composition. First, there are *sugar economies*, like Antigua, Barbados, Guyana (Demerara), St.Kitts and St.Lucia, where sugar exports make over half of total exports. Interestingly, the share increases considerably in Barbados and St.Kitts. Second, there is Jamaica, where the share of bananas is almost 50% in 1922 and surpasses it in 1927 (54%). However, Jamaica also produces a considerable amount of sugar (24 to 18%). Third, there is Grenada, which focusses mainly on Cacao (65 to 68%) and Dominica, which focusses on lime (Juice), which makes more than 90% of its exports. Fourth, there are *mixed*

[6] For example, Bulmer-Thomas (2012) underscores that between 1900 and 1960, sugar constituted more than 80% of Antigua and St. Kitts exports, petroleum products made up 67.7% of Trinidad and Tobago's exports, and sugar and molasses together represented 90% of Barbados' exports.

economies like, St.Vincent and Trinidad and Tobago, which do not focus on one export product. St.Vincent produces considerable amounts of molasses, arrowroot, and cotton. Similarly, Trinidad and Tobago exports sugar, cacao, asphalt, and oils, whereas the share of sugar exports decreases and the share of asphalt and especially oils increases rapidly between 1922 and 1927.

2.3 Tropical storms

Generally, one can roughly divide tropical cyclones into four groups. First, there are tropical depressions with wind speeds not exceeding 61 km/h, followed by tropical storms with wind speeds exceeding 61 km/h. In the Atlantic Ocean, storms exceeding 119 km/h are hurricanes (category 1), while major hurricanes (category three) have wind speeds exceeding 178 km/h. Historically, tropical storms have had profound impacts on the economies of the British Colonial Caribbean (see e.g. Schwartz 2015; Smith 2012; Morgan et al. 2022; Mohan and Strobl 2013). In general, hurricanes affect houses, infrastructure, and agriculture. Mohan and Strobl (2017) show that hurricanes negatively affect agricultural crops in the Caribbean. For the 1860 Hurricane Season, Dodds et al. (2009) show that the hurricanes destroyed personal property, transportation infrastructure as well as crops like sugar and cotton. During that time, Jamaica did not have a formal post-disaster strategy. The British colonial response of the time focused on maintaining dominance and fiscal conservatism. The approach relied on philanthropy rather than direct imperial government intervention (Webber 2018). Similarly, following natural disasters, local authorities did not offer targeted support. Instead, minimal aid was accessible through established poverty relief programmes, aimed at assisting those who were left destitute in the wake of a hurricane (Bryan 2000). Therefore, the duty of post-disaster rehabilitation mainly rested on private initiatives, as the government's participation was negligible.

Between 1922 and 1927 several tropical storms struck the islands in the Caribbean Basin. The first storm occurred in September 1922 which started as a category one hurricane near Dominica and became a category three hurricane close to Antigua. In the following days, the storm drifted eastward, struck Bermuda and went further north east until the English Channel. Two years later, the next category two hurricane passed between Antigua and Dominica and then to St. Kitts. Subsequently, the storm drifted eastward back to the Atlantic. The hurricane caused great damage throughout the Caribbean as more than 300 people died and thousands of houses were damaged (The Jamaica Gleaner 1924a).

The two most famous storms were both in 1926: *the 1926 Nassau Hurricane* and *the Great Miami Hurricane of 1926*, both of which impacted several islands in the Caribbean. *The 1926 Nassau Hurricane* initially manifested itself as a tropical storm with wind speeds of 90 to 110 km/h near Barbados, St. Lucia, and Dominica, before increasing to more than 165 km/h in Puerto Rico. Its peak wind speeds were recorded in Nassau (200 km/h), which also inspired its name, before it made landfall in Florida. The hurricane rendered several Nassau roads impassable and caused damage to houses, churches, and hotels (The Jamaica Gleaner 1926a).

A few months later, *the Great Miami Hurricane of 1926* struck Miami, earning the reputation as one of the most catastrophic events in U.S. history after the San Francisco fire (The Jamaica Gleaner 1926b). By September 14, the hurricane had already reached wind speeds of 167 km/h near Antigua, elevating it to a category two hurricane. Four days later, it made landfall in Miami with winds that exceeded 220 km/h (category four hurricane), where wind-related flooding caused extensive destruction (The Jamaica Gleaner 1926b). Generally, the Great Miami Hurricane of 1926 is recognised as one of the most costly storms in U.S. history (Pielke et al. 2008). Weinkle et al. (2018) estimates that it induced direct damage of approximately US$ 105 million.[7]

3 Data

3.1 Banking data

I created a historical banking panel from the Colonial Bank branches in the British Caribbean by digitizing semi-monthly data from August 1922 to December 1927, obtained from the *Assets & Liabilities of West Indies branches* report (Colonial Bank 1927). The panel includes data from 26 branches of the Colonial Bank, with 10 branches located in Jamaica (one closed in 1923 and another in 1924), 4 in Demerara (one closed in 1923), 3 in Trinidad (one closed in 1924), 2 in Barbados (one closed in 1925), as well as one each in Antigua, Grenada, Dominica, St. Kitts, St. Lucia, St. Vincent and Tobago (one closed in 1924). From the branches mentioned above, I excluded *Black River*, *Mahaica*, *May Pen*, *Princes Town*, *Speightstown*, *Suddie* and *Tobago* because there were less than *2/3* of the total number of observations available between 1922 and 1927.[8] I georeferenced the branches to assess whether it has been affected by a tropical storm. The spatial distribution of the Colonial Bank branches can be seen in Fig. 1.

In the specified time frame, the data set encompasses branch-specific data on various financial attributes: first, the aggregate balance across all clients' savings accounts (*SAV*) within a particular branch. Second, current account balance *(CAC)*, akin to checking accounts, indicates the funds available for transactions. As account holders may have positive and negative balances on their current accounts, *CAO* quantifies the total overdrawn sum or the extent of overdraft by clients. Hence, it is a proxy for short-term debt which might be used to smoothen consumption, which is expected to increase after a tropical storm as it was the case after Hurricane Katrina (Gallagher and Hartley 2017). The variable *DEP* denotes the capital that clients have allocated to time-bound deposits that accrue interest. The primary distinction between *savings* and *deposits* lies in their functionality and purpose. Although the former provides a readily accessible avenue for clients to move funds, the latter

7 This is approximately US$ 1.7 billion today.

8 Therefore, the final data set only contains observations from Antigua, Barbados, Berbice, Demerara, Dominica, Falmouth, Grenada, Kingston, Montego Bay, Morant Bay, Port Antonio, Port Maria, San Fernando, Savanna la Mar, St. Anns Bay, St. Kitts, St. Lucia, St. Vincent and Trinidad.

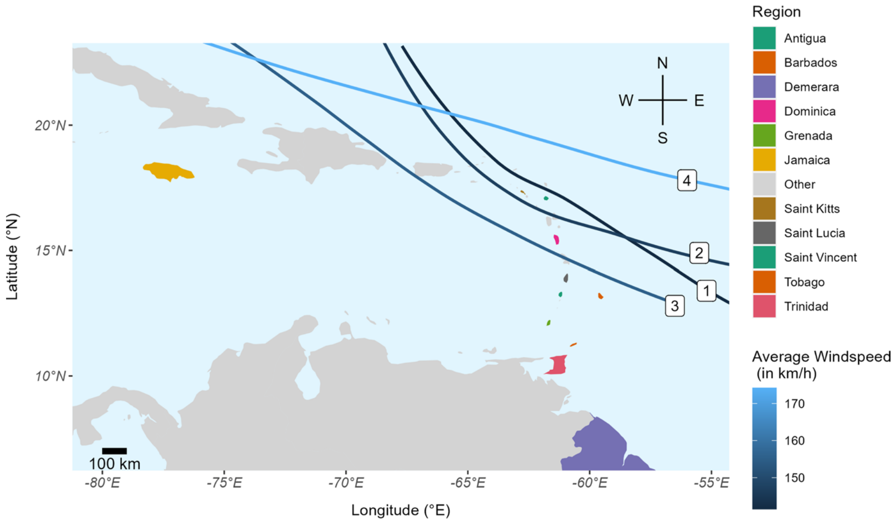


Fig. 1 Spatial Distribution of the tropical storms, using different shades of blue for the wind speed and different colours for the regions. In the figure, the four tropical storms are indicated by numbers ranging from 1 to 4: 1) September 1922, 2) August 1924, 3) July 1926 and 4) September 1926 (colour figure online)

represents a longer-term investment, typically earmarked for a specific duration and interest rate. Kass-Hanna et al. (2022) show that access to savings and borrowing increases financial resilience in South Asia and Sub Saharan Africa and Jacobsen et al. (2009) highlight the importance of access to a sufficient lump-sum after a disaster. For this reason, I included both *SAV* and *DEP* in the data set, as proxies for savings.

3.2 Storm data

The underlying storm data was created with the *HURDAT best tracks* from *National hurricane Centre's hurricane Database* which contains the position of the storm every 6 h, as well as intensity measures (highest wind speed) dating back to 1851. This data base has been used in several papers focusing on the impact of hurricanes. Mohan and Strobl (2013) estimated the economic impact of hurricanes on sugar exports in the Caribbean between 1700 and 1960. Ortiz Royero (2012) used the data base to assess the exposure of the Colombian Caribbean coast to hurricanes. Strobl (2011) analyzed the impact of hurricanes on the economic growth of coastal US counties and Boose et al. (2001) used *HURDAT* to estimate the historical regional impact of hurricanes in New England. According to Elsner and Jagger (2004), the *HURDAT* data are the most comprehensive and reliable record of hurricanes in the North Atlantic Ocean. To assess the impact of tropical storms on the local banking sector, a hurricane destruction index was created, based on a wind field model estimated using the *HURDAT best tracks* was created. The main assumption behind

Table 2 Summary statistics

Statistic	N	Mean	St. Dev	Min	Max
HURR	14	104.27	99.457	65.9	142
CAC	1,915	371,511.90	585,419.60	19,689.87	2,660,850.00
CAO	1,916	277,263.50	489,836.10	35.77	3,130,709.00
DEP	1,651	322,148.90	664,790.20	208.65	3,019,872.00
SAV	1,916	594,757.50	796,771.20	41,760.91	4,625,106.00
POPD	324	23.71	77.61	0.03	1,010.55

Summary statistics of the underlying variables. *HURR* are Hurricanes, *CAC* are Current Account Balances (credit), *DEP* Deposits, *CAO* are overdrawn Current Accounts and *SAV* are Savings Account Balances. *POPD* is the population density per km^2

the estimated destruction is that I assume that the wind speed at the branch office is the same as at the places where the clients live or where their plantations or houses are. To estimate wind speeds at the branch offices, I first interpolated the underlying six-hourly HURDAT-tracks to obtain more precise two-hourly locations of the underlying storms.

3.3 Summary statistics

Table 2 presents summary statistics for the banking variables and the wind speeds (denoted as *HURR*). During the study period, four storms with wind speeds exceeding 63 km/h made landfall at a minimum of one branch, yielding 14 observations. The average wind speed of these storms was 104.3 km/h, with the highest recorded wind speed being 142 km/h. The tracks of these four storms are shown in Fig. 1. Antigua, Dominica, St. Kitts and St. Lucia were the branches most affected by tropical storms, while branches in South America (Demerara) were typically unaffected by storms. The population density per km^2, *POPD*, also shows significant differences between areas with high and low population density. On average, 23.71 people live per km^2.[9]

Figure 2 illustrates the evolution of average *current account balances (CAC)*, the amount of *overdrawn current accounts (CAO)*, *deposits (DEP)* and *savings (SAV)* over time (in logs). In general, savings increase over time, especially in 1923. The amount of current account balances is the most volatile variable and shows a seasonal pattern with higher current account balances in summer and lower current account balances in winter. This is consistent with the idea that plantations receive income from selling their crops, such as sugar, after the harvest season (January to May), leading to increased balances. As the plantations begin to plant again, the expenditures increase, resulting in lower current account balances. The other variables do not show similar seasonal patterns. However, the general trend of the amount of current account balances is similar to the amount of deposits. What further strikes

[9] This is comparable to the population density of *Virginia* in the United States of America in the 21st century.

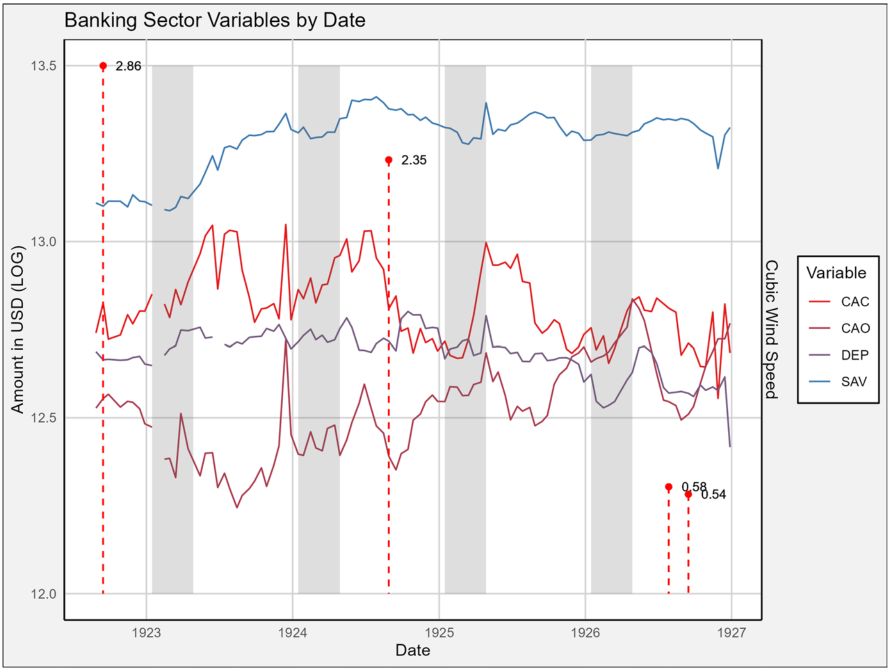


Fig. 2 This figure illustrate the evolution of the average value of the Banking Variables over time (in LOG and deflated in US$). *CAC* are Current Account Balances (credit), *CAO* are overdrawn Current Accounts, *DEP* are Deposits and *SAV* are Savings Account Balances. The red points are the cubic wind speeds (divided by 1 million) of the tropical storms occurring during the period. The grey shaded area represents the harvest season (January to May) (colour figure online)

out is that the amount of overdrawn current account balances decreases sharply at the beginning of 1923 but recovers quickly at the end of the same year.

Spatial variations of these four banking variables are presented in Table 3. Two key observations surface: first, the distribution across branches is quite disparate. The branches in Kingston, Trinidad, Barbados, and Demerara collectively account for 70 to 90% of the total amount of current account and savings balances, as well as the amount of overdrawn current accounts and deposits. Most importantly, these branches represent more than 75% of the average total balance sheet of the Colonial Bank in the British Caribbean, which stands at approximately US$ 29 million.[10] On the contrary, the shares of Port Antonio, Morant Bay and Port Maria from the total balance sheet are only 0.49%, 0.58%, and 0.74%, respectively. Secondly, the amount of overdrawn current accounts generally constitutes less than 20% of the branch balance sheet.[11] For the four largest branches, the proportion of overdrawn current accounts ranges from 12% in Demerara to 30% in Tobago. Furthermore, Kingston

[10] These branches contribute the following to the total balance sheet: Barbados (23%), Kingston (23%), Trinidad (18%), and Demerara (12.5%). For comparison, the fifth largest branch, St. Kitts, contributes just 3.2%.

[11] Notably high shares of overdrawn current accounts are seen in St. Lucia (41%).

Table 3 Banking variables

Branch	CAC	CAO	DEP	SAV
Antigua	170,489.07	70,961.35	16,015.19	337,278.39
Barbados	1,129,358.85	1,468,460.22	942,627.27	3,236,564.06
Berbice	79,717.81	100,485.91	13,363.34	254,477.02
Demerara	975,666.36	418,314.81	529,395.02	1,692,078.36
Dominica	47,420.63	92,916.00	52,990.10	186,952.48
Falmouth	38,053.43	1,187.216	159,838.67	104,192.01
Grenada	132,960.37	72,721.768	19,481.56	278,334.73
Kingston	1,642,646.61	828,984.26	2,739,390.33	1,380,402.65
Montego Bay	70,420.26	42,482.95	27,787.45	190,874.28
Morant Bay	47,140.70	2,759.26	7,631.71	109,435.49
Port Antonio	30,521.53	2,861.19	2,032.67	105,022.74
Port Maria	60,337.86	2,574.14	520.78	151,227.54
San Fernando	286,488.73	110,964.41	0	418,015.25
Savanna la Mar	63,347.92	2,461.99	130,004.83	62,882.95
St. Anns Bay	50,494.38	18,097.40	12,606.43	135,961.03
St. Kitts	132,615.06	123,432.24	281,155.02	387,771.19
St. Lucia	65,669.38	305,686.21	6,665.72	375,787.33
St. Vincent	107,748.85	26,473.39	42,938.70	516,056.69
Trinidad	1,930,512.63	1,565,005.07	339,653.71	1,378,156.50

Branch-level summary statistics of the underlying Banking Variables: *CAC* are Current Account Balances (credit), *DEP* are Deposits, *CAO* are overdrawn Current Accounts and *SAV* are Savings Account Balances

clients hold significant amounts of deposits of the Colonial Bank, comprising 42% of the branch's balance sheet compared to Trinidad's 7%. In contrast, clients in Barbados and Demerara frequently use the bank for savings (48% and 47%, respectively). However, the balance sheet compositions of Barbados, Demerara and Kingston appear more homogeneous when considering deposits and savings collectively, comprising roughly 62% of the balance sheets. However, Trinidad's balance sheet diverges considerably, as evidenced by its high share of overdrawn current account balances (30%), lower combined proportions of savings and deposits (33%), and higher percentage of current account balances (37%), compared to Barbados (17%) or Demerara (27%). Therefore, Table 3 discloses significant heterogeneity, not only in terms of the size of the branches, but also in terms of how clients use Colonial Bank.

Almost one third of the Colonial Bank's branches are located in Jamaica. Although this share is rather high, the weight of all Jamaican branches, except Kingston, is only 5.6% of the total balance sheet of the Colonial Bank. Therefore, this also indicates that many of the Jamaican clients were not clients of one of the smaller branches of the Colonial Bank, but in Kingston.

4 Methodology

4.1 Population-weighted destruction index

The impact of hurricanes has been assessed in many different ways in the literature. Some of them included a dummy variable when a storm made landfall or used the maximum wind speed (Schüwer et al. 2019; Boustan et al. 2012; Berlemann and Wenzel 2018; Mohan and Strobl 2013). However, these methods do not allow to estimate regional differences in the destruction. For this reason, I include a measure where the actual destruction of hurricanes depends on the windspeed.

I apply a population-weighted destruction index adapted from Strobl (2012)[12] to estimate the client's response to tropical storms. The index is constructed using localised wind speed estimates calculated from the actual paths of hurricanes using a wind field model. Specifically, the path of each hurricane is tracked in time and space and the Boose et al. (2004) model is applied to determine the wind speeds experienced in the Caribbean. This model, which takes into account factors such as peak wind speed, movement speed, direction, and landfall occurrence, provides the localised wind speed experienced at each landfall location for each moment in a hurricane's life. Instead of only estimating the wind speed at a branch, the population-weighted destruction index allows me to estimate the potential destruction caused in the area where the branch operates. To create the population-weighted destruction index, I utilised population data from 1920 that was obtained from the *History Database of the Global Environment (HYDE 3.2)* (Klein Goldewijk et al. 2017). This database provides population estimates at the level of a 0.083×0.083 degree grid, equivalent to 9.5×9.5 km.[13] Subsequently, I estimated the potential damage caused by storms at each grid cell. This damage is then weighted by its population in 1920 to give a population-weighted destruction index and thus the weighted destruction at each branch. Since these decadal population data predate all events of interest, endogeneity with regard to the population weights is arguably not a concern. Furthermore, the correlation coefficient between grid-level population data for the years 1920 and 1930 (post-event) is 0.999, suggesting the absence of any migration trends during the study period.

In order to create a population-weighted destruction index, I first use the two-hourly track data to estimate, according to Strobl (2012), the wind speed at every grid cell:

$$V = GF\left[V_m - S(1 - sin(T))\frac{V_h}{2}\right] \times \left[\left(\frac{R_m}{R}\right)^B exp\left(1 - \left(\frac{R_m}{R}\right)^B\right)\right]^{\frac{1}{2}} \tag{1}$$

Here, V_m signifies the maximum continual wind speed found anywhere within the hurricane, while T represents the angle formed by the hurricane's forward path and

[12] Which is based on the wind field model of Boose et al. (2004) which uses the equation of Holland (1980) for cyclostrophic wind and sustained wind velocity.

[13] In total, I used population data from 318 grid cells.

a radial line drawn from the hurricane centre to the point of interest, P (see Strobl 2012). The forward speed of the hurricane is represented by V_h. The radius of maximum winds is denoted as R_m, whereas R is the radial distance from the centre of the hurricane to the point P (for more details see Strobl 2012).

The population-weighted destruction index is calculated as follows and uses the wind speed $v_{j,t}$ in the grid cell j at time t, which was previously estimated in Equation (1):

$$DESTRUCTION_{i,r,t} = \left(\sum_{j=1}^{J} \int_0^{\tau} v_{j,t}^{\lambda} w_{i,j,r,t} \, dr \right) \text{ if } v_{j,t} > 63\text{km/h} \\ \text{and 0 otherwise} \tag{2}$$

Whereas $DESTRUCTION_{i,r,t}$ is the total estimated destruction caused by a storm r during the lifetime of the storm τ in the area of a branch i at time t. If there exists only one branch on an island, the area of the branch is the entire island. In the case where there is more than one branch exists, the island gets divided.[14]Emanuel (2005) noted that there is a correlation between the financial damages and energy release of hurricanes, which increases proportionately to the cube of their maximum wind speeds. This argues that the destructive potential of a hurricane can be roughly estimated by its highest recorded wind speed cubed (Emanuel 2005).[15]

For this reason, J, the set of grid cells in i and, according to Strobl (2012), λ is set to 3 (cubic). The population weight is $w_{i,j,r,t}$ and corresponds to the population in every cell of the grid in 1920 (Klein Goldewijk et al. 2017). Importantly, I include only wind speeds exceeding 63 km/h (i.e., tropical storms) in the analysis.

4.2 Econometric specification

In order to quantify the impact of the storms on the banking variables, I use the following econometric specification:

$$LOG(BANK_{i,t}) = \beta_0 + \sum_{k=0}^{p} \beta_{k+1} \cdot DESTRUCTION_{i,t-k} + \alpha_z + \delta_m + \theta_i + \epsilon_{i,t} \tag{3}$$

where α_z and δ_m are yearly and monthly fixed effects, θ_i are branch fixed effects, $LOG(BANK_{i,t})$ is the log of the banking variable and $DESTRUCTION$ is the population weighted destruction index at branch i at t,..., $t-k+1$. I use robust standard errors.

In this study, I also account for branch-specific immutable effects represented by θ_i and common shocks specific to the year and month denoted by α_z and δ_m. Monthly fixed effects allow me to capture seasonal variations, i.e. intensive rainfalls, price shocks of commodities, or seasonal patterns in labour demand/supply. The yearly fixed

[14] In the case of Barbados, I divided Barbados in two parts. The Speightstown-Branch covers the northern part, and the Bridgetown-Branch covers the southern part.

[15] This index was also applied by several other papers i.e. Strobl (2012 2011), Bertinelli and Strobl (2013), Brei et al. (2019), Elliott et al. (2023), Mohan and Strobl (2017).

effects however capture year-specific impacts, i.e. years with extreme droughts, the introduction of tariffs or the incorporation of laws. One may also want to note that the econometric methodology is closely related to that used by Mohan and Strobl (2021) and Elliott et al. (2023). It as such posits that the local distribution of potential damage caused by tropical storms, or at least the perception thereof, remains constant over time. Given the relatively short time in the analysis this is likely to hold true. Thus, by accounting for both branch specific, time-invariant, and time fixed effects, equation (3) in the paper isolates the variation in destruction that can reasonably be considered as random, unanticipated realisations from the distribution of potential damages from storms (Mohan and Strobl 2021; Elliott et al. 2023). This allows a causal interpretation of the coefficients on $DESTRUCTION_{t-k}$.

In the underlying panel models, several half-monthly lags are included. This approach is similar to the approach applied in current papers which estimate the effect of environmental shocks on banking variable (Noth and Schüwer 2023; Blickle et al. 2021; Walker et al. 2023). The motivation for using a model with several lags is due to the fact that lags are crucial as tropical storms might not immediately affect certain variables or even affect them over a longer period. Therefore, applying a certain number of lags helps to estimate the effect of a tropical storm on the banking variables. In the underlying specification, 18 lags (that is, nine months) were applied. However, different numbers of lags were applied to investigate whether the results are robust. As tropical storms are random exogenous shocks and no tropical storm warning systems were in place, people could not anticipate a tropical storm and try to mitigate damage. Moreover, as the econometric specification is similar to those of Mohan and Strobl (2021), it is worth mentioning that the estimated population weighted potential destruction index can be argued to be exogenously derived. Although clients of the Colonial Bank, in theory, might position assets within countries cognisant of which regions are more prone or less susceptible to storm damage, once we adjust for branch-specific fixed effects, what arguably remains are random manifestations from the local distribution of potential hurricane damage.

5 Results

5.1 Spatial variation of the underlying storms

As can be seen in Table 4, only four branches were affected by the underlying storms, indicating considerable spatial variation. The estimated wind speed at the branch for the first and second storms was significantly higher than for the third and fourth storms (both in the same year). For the first and second storms, the mean non-zero wind speed measured at the branches was 115.8 km/h, compared to 74.9 km/h for the third and fourth storms. The maximum wind speed was also much higher, 142 km/h compared to 83.4 km/h. More importantly, the first and second storms caused even more destruction because they hit more populated areas, so that the average destruction index was 9.5 compared to 0.86 (more than ten times higher). The maximum destruction is even 15 times higher (25.3 compared to 1.8, which is

Table 4 Storms

Branch	Storm 1	Storm 2	Storm 3	Storm 4
Antigua	143	133	65.9	81.4
Barbados	0	0	0	0
Berbice	0	0	0	0
Demerara	0	0	0	0
Dominica	87.7	108	83.4	0
Falmouth	0	0	0	0
Grenada	0	0	0	0
Kingston	0	0	0	0
Montego Bay	0	0	0	0
Morant Bay	0	0	0	0
Port Antonio	0	0	0	0
Port Maria	0	0	0	0
San Fernando	0	0	0	0
Savanna la Mar	0	0	0	0
St. Anns Bay	0	0	0	0
St. Kitts	134	133	68.8	73.4
St. Lucia	0	67.5	73.3	0
St. Vincent	0	0	0	0
Trinidad	0	0	0	0

Estimated wind speed (in km/h) at the branches of the four underlying storms. Storm 1 *(1922-09-15)*, Storm 2 *(1924-08-28)*, Storm 3 *(1926-07-28)*, and Storm 4 *(1926-09-15)*

even lower than the average of the first and second storms). In general, it can be said that there were considerable differences between storms and branches.

The index shows heterogeneous destruction over the area. In the case of the second storm in the sample, I confirmed that the heterogeneity in the index was also found in the *Jamaican Gleaner*. The Jamaica Gleaner (1924a) shows that there was variation in damage so that the Virgin Islands were hit very hard and the storm caused significant damage. The storm also hit St Kitts (The Jamaica Gleaner 1924b) and Dominica, but caused no damage to Jamaica (The Jamaica Gleaner 1924c). Thus, the articles in the *Jamaican Gleaner* show that the variation in estimated destruction seems plausible.

5.2 Impact on banking variables

In the first step of the analysis, I estimate the effect of tropical storms on branch-level banking variables by using fixed effects panel regression models from equation (2). Table 5 shows the results from the effect of tropical storms on the banking variables. I focus on the effect on the log of the specific variable. Right after the storm, the amount of current account balances increases and becomes insignificant in the two to seven months afterwards. The intuition for the initial positive effect comes

Table 5 Effect of tropical storms on banking variables

Banking Variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
Variables				
$DESTRUCTION_t$	0.0163***	0.0138***	0.0020	0.0185***
	(0.0030)	(0.0032)	(0.0033)	(0.0046)
$DESTRUCTION_{t-0.5m}$	0.0089***	0.0154***	0.0025	0.0176***
	(0.0023)	(0.0038)	(0.0030)	(0.0046)
$DESTRUCTION_{t-1m}$	0.0105**	0.0118***	0.0008	0.0183***
	(0.0043)	(0.0045)	(0.0032)	(0.0065)
$DESTRUCTION_{t-1.5m}$	0.0086*	0.0111**	−0.0002	0.0159***
	(0.0051)	(0.0048)	(0.0023)	(0.0050)
$DESTRUCTION_{t-2m}$	0.0081	0.0048	0.0008	0.0156***
	(0.0053)	(0.0074)	(0.0022)	(0.0052)
$DESTRUCTION_{t-2.5m}$	0.0054	0.0093	0.0009	0.0149***
	(0.0060)	(0.0066)	(0.0017)	(0.0041)
$DESTRUCTION_{t-3m}$	0.0028	0.0145***	−0.0001	0.0147***
	(0.0069)	(0.0047)	(0.0018)	(0.0042)
$DESTRUCTION_{t-3.5m}$	−0.0019	0.0252***	−0.0008	0.0119***
	(0.0067)	(0.0068)	(0.0020)	(0.0037)
$DESTRUCTION_{t-4m}$	9.51×10^{-6}	0.0321***	0.0002	0.0138***
	(0.0049)	(0.0054)	(0.0021)	(0.0034)
$DESTRUCTION_{t-4.5m}$	0.0005	0.0313***	−0.0015	0.0147***
	(0.0069)	(0.0052)	(0.0014)	(0.0033)
$DESTRUCTION_{t-5m}$	0.0038	0.0268***	−0.0020	0.0177***
	(0.0052)	(0.0060)	(0.0015)	(0.0031)
$DESTRUCTION_{t-5.5m}$	0.0007	0.0293***	−0.0005	0.0154***
	(0.0045)	(0.0048)	(0.0012)	(0.0044)
$DESTRUCTION_{t-6m}$	0.0038	0.0298***	−0.0010	0.0136***
	(0.0054)	(0.0038)	(0.0016)	(0.0039)
$DESTRUCTION_{t-6.5m}$	0.0035	0.0353***	-1.65×10^{-5}	0.0123***
	(0.0063)	(0.0095)	(0.0017)	(0.0038)
$DESTRUCTION_{t-7m}$	0.0055	0.0223***	0.0010	0.0127***
	(0.0087)	(0.0030)	(0.0012)	(0.0039)
$DESTRUCTION_{t-7.5m}$	0.0131**	0.0195***	0.0023**	0.0125***
	(0.0061)	(0.0040)	(0.0011)	(0.0039)
$DESTRUCTION_{t-8m}$	−0.0018	0.0144***	0.0012	0.0159*
	(0.0079)	(0.0045)	(0.0012)	(0.0096)
$DESTRUCTION_{t-8.5m}$	0.0115*	0.0137***	0.0034***	0.0147***
	(0.0064)	(0.0033)	(0.0012)	(0.0048)
$DESTRUCTION_{t-9m}$	0.0138*	0.0091***	0.0035***	0.0148***
	(0.0083)	(0.0033)	(0.0009)	(0.0050)

Table 5 (continued)

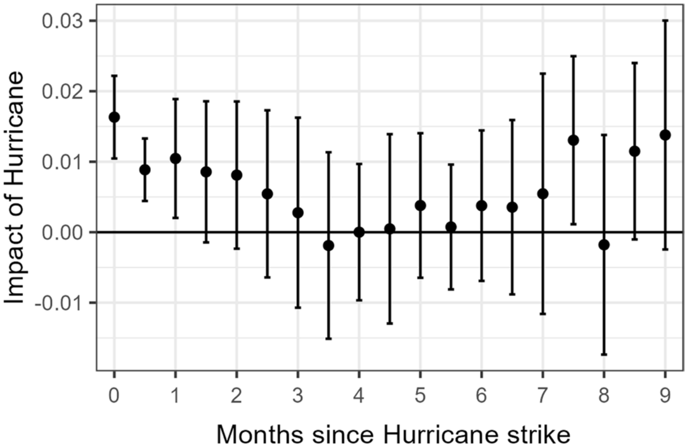
Banking Variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
Fixed-effects				
Factor (month)	Yes	Yes	Yes	Yes
Factor (year)	Yes	Yes	Yes	Yes
Factor (Location)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,650	1,650	1,650	1,650
R^2	0.97042	0.92876	0.98555	0.96921
Within R^2	0.01946	0.01690	0.00326	0.02415

Heteroskedasticity-robust standard-errors in parentheses

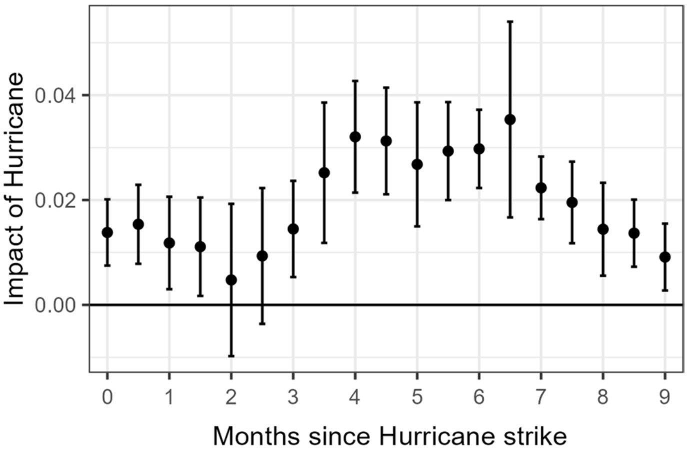
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

from the fact that clients might send money from accounts in other parts of the British Empire to their accounts at the affected branches. Subsequently, clients use their current accounts to pay for the immediate damages caused by the storm. These findings are in line with the current literature suggesting that after a tropical storm deposits decrease (Deryugina et al. 2014; Brei et al. 2019; Sawada and Shimizutani 2008) or that withdrawals increase (Bayangos et al. 2021; Do et al. 2021; Nguyen et al. 2023; Bos et al. 2022; Brei et al. 2019; Do et al. 2022; Allen et al. 2022). A further source to obtain liquidity was simply to overdraw current accounts. In fact, the results show that the clients did indeed overdraw their current accounts, which is consistent with Barth et al. (2019), Barth et al. (2022), Bos et al. (2022), Berg and Schrader (2012), Koetter et al. (2020). As it might take some time to send money from other accounts to the account in the affected area, clients directly increase the amount of overdrawn current account as it might be an easy way to pay for the repair of damage caused by the tropical storm. However, the effect becomes insignificant one month after the tropical storm and becomes significant again three months after the tropical storm. Moreover, the results further show that both Client's deposits increase in the months following a tropical storm. On first glance, one would expect a different reaction. However, Barth et al. (2022), Barth et al. (2019) and Cortés and Strahan (2017) emphasise that branches in affected regions increase interest rates on deposits, which in turn should attract more deposits to prevent the bank from a negative funding shock as the demand for loans increases. Therefore, the results show that the affected branches of the Colonial Bank were able to attract both, more deposits and savings, to prevent a funding shock. However, the effect on savings account balances becomes significantly positive 7.5 months after a tropical storm. The results are further illustrated in Figs. 3 and 4.

The results of the econometric analysis indicate that the impact of tropical storms on the banking sector in the British West Indies during the early 20th century was significant and multidimensional. In the aftermath of the tropical storms, clients overdrew their current accounts to finance the damages caused by



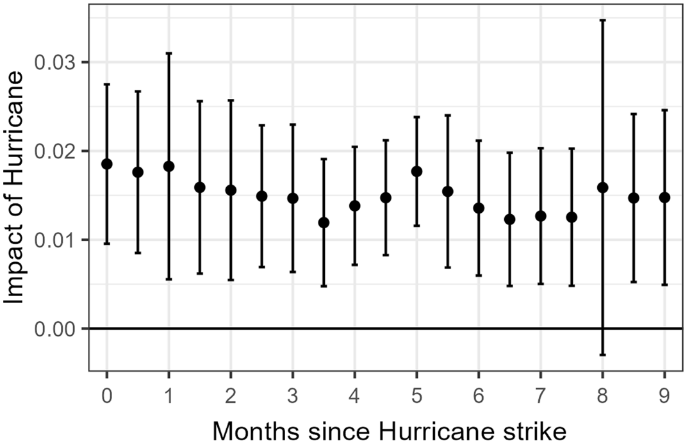
(a) Current Account Balances (in logs)



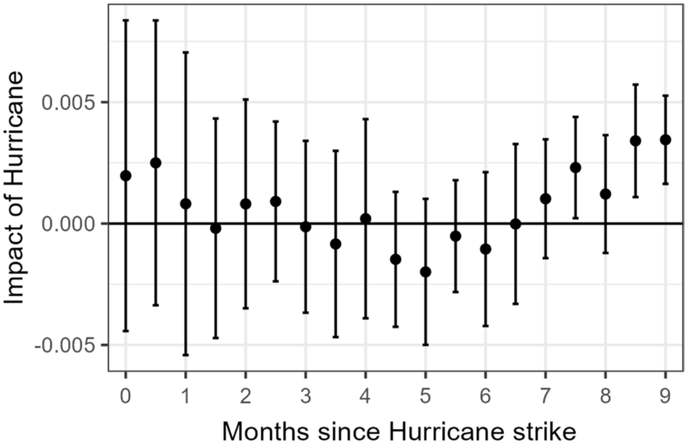
(b) Overdrawn Current Accounts (in logs)

Fig. 3 This figure reports the estimated impact of tropical storms on Current Account Balances and overdrawn Current Accounts (both in logs) and the corresponding 95% confidence intervals between 1922 and 1927

the natural disaster or transferred funds to affected branches, which caused an initial increase in their current account balances. The affected branches of Colonial Bank also manage to attract additional deposits and savings to avoid funding shocks, although the effect on savings is generally insignificant. Therefore, the results suggest that initially clients overdraw their current accounts to pay for the immediate damages caused by the storm. At the same time, clients send money to the branches, which they in turn use to repay their negative current account balances in the month following the tropical storm. Therefore, the effect on current account balances becomes insignificant. To repair more severe damage, clients



(a) Deposits (in logs)



(b) Savings Account Balances (in logs)

Fig. 4 This figure reports the estimated impact of tropical storms on Deposits and Savings Account Balances (both in logs) and the corresponding 95% confidence intervals between 1922 and 1927

need more capital, which they obtain from two sources. First, after transferring money from other branches and banks causing higher deposits, they gradually decrease in the first three months by over US$ 17,000 for the average non-zero potential damage. Second, they increase the amount of overdrawn current account balances three months after the tropical storm.

In a further robustness check, six additional lagged values of *HURR* (up to $HURR_{t-12m}$) were incorporated in Table 6. By including up to 24 lags (12 months), the results slightly alter as the initial effect on the amount of current account balances and the amount of overdrawn current accounts gain more significance and become slightly higher. For the amount of current account balances, the amount of

Table 6 Robustness: effect of tropical storms on banking variables

Model	CAC (1)	CAC (2)	CAO (3)	CAO (4)	SAV (5)	SAV (6)	DEP (7)	DEP (8)
Variables								
$HURR_t$	0.0557	0.0821**	0.0772*	0.1002**	0.0050	0.0152	0.1225***	0.1345***
	(0.0378)	(0.0372)	(0.0426)	(0.0435)	(0.0252)	(0.0254)	(0.0449)	(0.0453)
$HURR_{t-0.5m}$	0.0577*	0.0830***	0.0824**	0.1044***	0.0192	0.0291	0.1122**	0.1237**
	(0.0317)	(0.0319)	(0.0390)	(0.0391)	(0.0221)	(0.0222)	(0.0483)	(0.0485)
$HURR_{t-1m}$	0.0578	0.0823*	0.0635	0.0852**	−0.0055	0.0041	0.1245**	0.1359**
	(0.0438)	(0.0435)	(0.0423)	(0.0424)	(0.0195)	(0.0197)	(0.0593)	(0.0597)
$HURR_{t-1.5m}$	0.0557	0.0787*	−0.0030	0.0179	−0.0020	0.0070	0.0995**	0.1107**
	(0.0453)	(0.0448)	(0.0651)	(0.0656)	(0.0205)	(0.0208)	(0.0505)	(0.0504)
$HURR_{t-2m}$	0.0394	0.0621	0.0182	0.0386	−0.0008	0.0080	0.1065**	0.1174**
	(0.0514)	(0.0510)	(0.0599)	(0.0606)	(0.0155)	(0.0158)	(0.0495)	(0.0495)
$HURR_{t-2.5m}$	0.0222	0.0434	0.0843*	0.1033**	−0.0047	0.0035	0.0883*	0.0983**
	(0.0581)	(0.0581)	(0.0448)	(0.0445)	(0.0150)	(0.0152)	(0.0457)	(0.0458)
$HURR_{t-3m}$	−0.0079	0.0145	0.1459**	0.1658**	−0.0088	-6.32×10^{-5}	0.0778	0.0883*
	(0.0567)	(0.0571)	(0.0659)	(0.0665)	(0.0157)	(0.0159)	(0.0483)	(0.0483)
$HURR_{t-3.5m}$	3.52×10^{-5}	0.0229	0.2326***	0.2526***	−0.0022	0.0067	0.0845**	0.0950**
	(0.0452)	(0.0458)	(0.0505)	(0.0509)	(0.0173)	(0.0176)	(0.0408)	(0.0412)
$HURR_{t-4m}$	0.0218	0.0437	0.2422***	0.2614***	−0.0123	−0.0038	0.1091***	0.1191***
	(0.0578)	(0.0586)	(0.0467)	(0.0475)	(0.0119)	(0.0121)	(0.0336)	(0.0346)
$HURR_{t-4.5m}$	0.0267	0.0510	0.2232***	0.2445***	−0.0109	−0.0015	0.1397***	0.1508***
	(0.0495)	(0.0499)	(0.0507)	(0.0513)	(0.0130)	(0.0134)	(0.0321)	(0.0331)
$HURR_{t-5m}$	0.0090	0.0333	0.2232***	0.2445***	−0.0019	0.0075	0.1208***	0.1319***
	(0.0370)	(0.0372)	(0.0410)	(0.0421)	(0.0112)	(0.0115)	(0.0395)	(0.0404)
$HURR_{t-5.5m}$	0.0055	0.0294	0.2646***	0.2856***	−0.0032	0.0061	0.1392***	0.1501***
	(0.0501)	(0.0506)	(0.0289)	(0.0306)	(0.0103)	(0.0107)	(0.0377)	(0.0388)
$HURR_{t-6m}$	0.0218	0.0458	0.2884***	0.3094***	−0.0034	0.0059	0.1239***	0.1348***
	(0.0496)	(0.0498)	(0.0786)	(0.0795)	(0.0158)	(0.0162)	(0.0352)	(0.0365)
$HURR_{t-6.5m}$	0.0182	0.0420	0.1870***	0.2078***	0.0039	0.0132	0.0898***	0.1007***
	(0.0635)	(0.0635)	(0.0271)	(0.0289)	(0.0147)	(0.0150)	(0.0346)	(0.0360)
$HURR_{t-7m}$	0.1076**	0.1329***	0.1627***	0.1844***	0.0157	0.0254**	0.0815**	0.0926**
	(0.0493)	(0.0497)	(0.0320)	(0.0333)	(0.0115)	(0.0120)	(0.0387)	(0.0401)
$HURR_{t-7.5m}$	0.0547	0.0803	0.1579***	0.1798***	0.0172**	0.0270***	0.0847	0.0959
	(0.0690)	(0.0695)	(0.0424)	(0.0436)	(0.0088)	(0.0090)	(0.0582)	(0.0594)
$HURR_{t-8m}$	0.0630	0.0892	0.1329***	0.1556***	0.0234**	0.0336***	0.0888	0.1006
	(0.0711)	(0.0718)	(0.0347)	(0.0365)	(0.0115)	(0.0119)	(0.0636)	(0.0646)
$HURR_{t-8.5m}$	0.0859	0.1117**	0.0800***	0.1024***	0.0303***	0.0404***	0.0936**	0.1052**
	(0.0561)	(0.0566)	(0.0274)	(0.0296)	(0.0079)	(0.0084)	(0.0472)	(0.0485)
$HURR_{t-9m}$	0.1235**	0.1500**	0.0595	0.0827**	0.0338***	0.0441***	0.0865*	0.0986**
	(0.0614)	(0.0621)	(0.0381)	(0.0403)	(0.0064)	(0.0069)	(0.0484)	(0.0496)
$HURR_{t-9.5m}$		0.1371**		0.0917**		0.0466***		0.0324
		(0.0566)		(0.0434)		(0.0102)		(0.0450)
$HURR_{t-10m}$		0.1323***		0.0870**		0.0447***		0.0317
		(0.0422)		(0.0389)		(0.0086)		(0.0446)

Table 6 (continued)

Model	CAC (1)	CAC (2)	CAO (3)	CAO (4)	SAV (5)	SAV (6)	DEP (7)	DEP (8)
$HURR_{t-10.5m}$		0.1218***		0.0728**		0.0461***		0.0418
		(0.0299)		(0.0370)		(0.0081)		(0.0398)
$HURR_{t-11m}$		0.0869**		0.0991**		0.0431***		0.0402
		(0.0434)		(0.0409)		(0.0108)		(0.0396)
$HURR_{t-11.5m}$		0.0890***		0.1118***		0.0399***		0.0797
		(0.0334)		(0.0366)		(0.0104)		(0.0766)
$HURR_{t-12m}$		0.1008***		0.1212***		0.0384***		0.0784
		(0.0341)		(0.0328)		(0.0113)		(0.0769)
Fixed-effects								
Factor (month)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factor (year)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factor (Location)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,650	1,650	1,650	1,650	1,650	1,650	1,650	1,650
R^2	0.97021	0.97074	0.92854	0.92867	0.98556	0.98567	0.96895	0.96901
Within R^2	0.01261	0.02995	0.01390	0.01565	0.00335	0.01134	0.01595	0.01775

Heteroskedasticity-robust standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

overdrawn current accounts, and savings account balances, the impact remains significant up to 12 months post-strike, suggesting that Colonial Bank's clients indeed escalated their lending over a more extended period, presumably for investments or repairs. In addition, it indicates that clients were engaging in precautionary saving, as evident from the increase in the balances of the savings account. In the case of deposits, the results remain unchanged. However, the inclusion of additional lags is problematic as storms from two seasons may overlap.

5.3 Economic significance

The results are also economically significant. The direct impact of the average non-zero potential damage initially increases current account balances by 13.1%, although this effect dissipates in the following two months. Taking the average current account balance per branch, this can be translated into an initial increase in current account balances of roughly US$ 48,600, indicating that clients were able to send money from either other accounts at different branches of the Colonial Bank, accounts at other banks or to obtain loans from merchants, private individuals, or even banks located outside the British West Indies. The amount of overdrawn current account increases in the first month by approximately 8.9 to 12.4%, becomes zero before gradually increasing to 28.6% half a year after the storm. Afterwards, the effect becomes smaller, so that nine months after a tropical storm strikes, the amount of overdrawn current accounts is roughly 7.3% higher compared to before the storm. Therefore, this results in overdrawn current account balances of US$ 33,000 to US$ 46,000 in the first month and up to US$ 106,000 half a year after the storm and US$ 27,000 nine months after the storm. In the case of deposits, a tropical storm increases them by 9.5% (US$ 30,600) to 14.9% (US$ 48,000) over the first nine months. Therefore, the results suggest that the affected branches of the Colonial Bank were able to attract further deposits after disasters, which prevented them from experiencing a negative funding shock.

However, the banking variables are also mutually intertwined. Therefore, following the estimated value of average non-zero population weighted destruction, the direct aggregate inflow of client assets per affected branch is approximately US$ 80,000,[16] while the amount of overdrawn current accounts increases by US$ 25,460, culminating in *net inflows* of US$ 54,600. *Net inflows* continuously decrease afterward and become negative 3.5 months after the hurricane strike. This comes from the fact that the amount of both current account balances and deposits steadily decreased, while clients increased borrowing through overdrawing current accounts. Hence, the results suggest that after an average tropical storm, clients amplified borrowing, in contrast to transferring assets from accounts at other branches or banks. Furthermore, it further implies that the additional inflows after the hurricane were directly used to repair damages caused by the hurricane.

Six and a half months after a strike, customers in affected branches have increased their debts by almost US$ 66,000 while the amount of assets increased only by US$ 26,000, culminating in *outflows* of almost US$ 40,000. Hence, the results suggest that roughly half a year after a strike, clients of an affected branch spent over US$ 40,000 on direct or indirect damage from tropical storms. However, eight months after a tropical storm, the amount of overdrawn current accounts is less than half of its value from 6.5 months after the storm. At the same time, clients increased their deposits by almost one third. Half a month later, clients increase their savings by over US$ 13,000, which slightly increases a further half month later. Therefore, nine months after the hurricane strike, overdrawn current accounts are almost US$ 17,000 higher compared to their values before the shock. However, this is only approximately the amount of the clients net inflows.[17] As *net inflows* increased by approximately US$ 63,000, clients from the Colonial Bank repaid their debts which they owed to the Colonial Bank and were, at the same time, able to increase their assets.

5.4 Robustness checks

5.4.1 Fisher randomization test

To assess the robustness of the findings, I used a Fisher randomization test (Fisher et al. 1937). To this end, tropical storms were randomly assigned across banks and

[16] The inflows are roughly US$ 40,300 from current account balances, US$ 0 from savings account balances and US$ 39,700 from deposits.

[17] Current account balances increased by US$ 34,000, savings by almost US$ 14,000 deposits by US$ 31,700.

time, with the same model as mentioned above then estimated. This procedure was repeated 1,000 times, resulting in 1,000 *t-values* for each coefficient. These were then added to obtain the *Test Statistics*. The *t-statistics* of the 43 significant coefficients are presented in Table 7, accompanied by the *t-statistics* from the Fisher randomization test (CAC_f, CAO_f, SAV_f and DEP_f). Out of the 43 *t-values*, one *t-values*[18] from the Fisher randomization test have both the minimum magnitude to be deemed significant and also has the correct sign. Hence, the effects can generaly be determined to be causal rather than random. Especially in the case of the amount of current account balance, deposits and savings. In the case of overdrawn current account balances, I would generally say that the effects are causal, especially as out of the 19 coefficients of the Fisher randomization test only one is significant (5%) could have happened purely by chance.

5.4.2 Cubic wind speed

An important concern might be whether the results from the population-weighted destruction index overestimate the impact of tropical storms of the clients from the Colonial Bank. For this reason, I additionally estimate the regression by using the cubic wind speed estimated at the branches, instead of using a a population-weighted destruction index. Therefore, the regression model becomes the following:

$$LOG(BANK_{i,t}) = \beta_0 + \sum_{k=0}^{p} \beta_{k+1} \cdot HURR_{i,t-k} + \alpha_z + \delta_m + \theta_i + \epsilon_{i,t} \tag{4}$$

The results in Table 8 show similar signs compared to the ones obtained in the baseline model in Sect. 5.2. The odd column number is always the model with 18 lags and the even column number represents the model with 24 lags. Taking the average estimated wind speed (104.3 km/h) causes current account balances to increase by 9.3 to 9.8% in the first 1.5 months after a storm and then becomes zero. Moreover, such a storm increases the amount of overdrawn current accounts by 10.1 to 12.5% in the same period, becomes zero, and increases again by up to 41.1% in the following five months, which is slightly less compared to the results from the baseline specification. Additionally, deposits increase between 10.5 and 18.4% in the following nine months, and savings increase up to 5.1% between 7.5 and 9 months after a storm. Therefore, the impact of *DESTRUCTION* on savings and deposits is always slightly smaller compared to the results in the baseline specification. Therefore, the differences between the results in Table 5 are mostly caused by the differences in the distributions of the two underlying variables, as *DESTRUCTION*, compared to *HURR*, gives over-proportional high weights to tropical storms that affect a higher share of the population with a higher wind speed. Including further lags generally increases the size of the effect by up to 10% depending on the banking variable. However, the same pattern was already visible in the case of the population-weighted destruction index in section 5.2. However, the estimated effects obtained with the cubic wind speed are similar to the ones obtained with the population

[18] The impact of a *HURR* at $t - 4.5m$ on *CAO*. The remaining *t*-values are smaller than 1.96.

Table 7 Fisher randomization test: obtained t-Values

	CAC_f	CAC	CAO_f	CAO	SAV_f	SAV	DEP_f	DEP
$DESTRUCTION_t$	0.99	5.43	−1.14	4.31			0.50	4.02
$DESTRUCTION_{t-0.5m}$	0.93	3.87	−0.89	4.05			0.41	3.83
$DESTRUCTION_{t-1m}$	0.99	2.44	−0.83	2.62			0.36	2.82
$DESTRUCTION_{t-1.5m}$	−0.20	1.68	−0.26	2.31			0.40	3.18
$DESTRUCTION_{t-2m}$							0.37	3.00
$DESTRUCTION_{t-2.5m}$							0.31	3.63
$DESTRUCTION_{t-3m}$			0.07	3.09			0.49	3.50
$DESTRUCTION_{t-3.5m}$			−0.66	3.71			0.64	3.22
$DESTRUCTION_{t-4m}$			0.62	5.94			0.31	4.06
$DESTRUCTION_{t-4.5m}$			2.36	6.02			0.57	4.45
$DESTRUCTION_{t-5m}$			1.13	4.47			0.50	5.71
$DESTRUCTION_{t-5.5m}$			1.09	6.10			0.47	3.50
$DESTRUCTION_{t-6m}$			0.29	7.84			1.52	3.49
$DESTRUCTION_{t-6.5m}$			0.03	3.72			1.39	3.24
$DESTRUCTION_{t-7m}$			0.07	7.43			0.96	3.26
$DESTRUCTION_{t-7.5m}$	−0.64	2.14	−1.02	4.88	1.93	2.09	0.95	3.21
$DESTRUCTION_{t-8m}$			−1.22	3.20			0.67	1.66
$DESTRUCTION_{t-8.5m}$	0.15	1.80	−0.83	4.15	0.47	2.83	0.52	3.06
$DESTRUCTION_{t-9m}$	−1.68	1.66	−0.27	2.76	1.39	3.89	0.60	2.96

This table shows the t-Values for the Banking Variables (CAC, CAO, SAVINGS and DEP) as well as the ones obtained from the Fisher Randomization Test (CAC_f, CAO_f, SAV_f and DEP_f)

weighted destruction index. The initial estimated effect of the population-weighed destruction index (cubic wind speed) on the amount of current account balances is 13.1% (9.3 to 9.8%), on the amount of overdrawn current accounts is between 8.9 to 12.4% (10.1 to 12.1%) and on deposits is between 9.5 to 14.9% (10.5 and 18.4%). Furthermore, using the population weighted destruction index (cubic wind speed) estimates an increase in the amount of overdrawn current account balances by up to 28.6% (41.1%) and an increase in savings account balances by up to 2.3% (5.1%). As the magnitude of the results is generally comparable, it shows that the estimations are robust with respect to changing the functional form. More precisely the results are robust with respect to only using the estimated cubic wind speed at the branches instead of applying a population-weighted destruction index.

5.4.3 Changes in banking system

As the focus is on a brief period, it is, as I am aware, unlikely that the banking system underwent significant changes within only five years. Table 4 indicates that only a limited number of branches were impacted, therefore spatial variation across the branches exists. However, it should be noted that the attention is on the average impact of the hurricanes, rather than on the individual event studies. To nevertheless verify this indirectly, Table 9 presents an additional regression analysis I conducted. It includes

Table 8 Robustness: effect of tropical storms on banking variables

Banking Variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
Variables				
$DESTRUCTION_t$	0.0198***	0.0162***	0.0031	0.0211***
	(0.0030)	(0.0034)	(0.0033)	(0.0047)
$DESTRUCTION_{t-0.5m}$	0.0123***	0.0177***	0.0036	0.0201***
	(0.0022)	(0.0040)	(0.0030)	(0.0047)
$DESTRUCTION_{t-1m}$	0.0136***	0.0140***	0.0019	0.0207***
	(0.0043)	(0.0046)	(0.0032)	(0.0066)
$DESTRUCTION_{t-1.5m}$	0.0115**	0.0131***	0.0008	0.0181***
	(0.0051)	(0.0049)	(0.0024)	(0.0050)
$DESTRUCTION_{t-2m}$	0.0110**	0.0068	0.0018	0.0179***
	(0.0053)	(0.0075)	(0.0022)	(0.0051)
$DESTRUCTION_{t-2.5m}$	0.0084	0.0114*	0.0019	0.0172***
	(0.0061)	(0.0067)	(0.0017)	(0.0041)
$DESTRUCTION_{t-3m}$	0.0055	0.0164***	0.0008	0.0167***
	(0.0070)	(0.0047)	(0.0019)	(0.0043)
$DESTRUCTION_{t-3.5m}$	0.0012	0.0273***	0.0002	0.0142***
	(0.0069)	(0.0069)	(0.0020)	(0.0038)
$DESTRUCTION_{t-4m}$	0.0031	0.0342***	0.0012	0.0161***
	(0.0051)	(0.0056)	(0.0022)	(0.0036)
$DESTRUCTION_{t-4.5m}$	0.0034	0.0333***	−0.0005	0.0169***
	(0.0070)	(0.0053)	(0.0014)	(0.0035)
$DESTRUCTION_{t-5m}$	0.0070	0.0290***	−0.0009	0.0201***
	(0.0053)	(0.0062)	(0.0016)	(0.0033)
$DESTRUCTION_{t-5.5m}$	0.0039	0.0316***	0.0005	0.0178***
	(0.0046)	(0.0049)	(0.0012)	(0.0045)
$DESTRUCTION_{t-6m}$	0.0070	0.0320***	8.73×10^{-6}	0.0160***
	(0.0055)	(0.0040)	(0.0017)	(0.0041)
$DESTRUCTION_{t-6.5m}$	0.0068	0.0376***	0.0011	0.0148***
	(0.0064)	(0.0096)	(0.0017)	(0.0040)
$DESTRUCTION_{t-7m}$	0.0087	0.0246***	0.0021	0.0152***
	(0.0088)	(0.0033)	(0.0013)	(0.0041)
$DESTRUCTION_{t-7.5m}$	0.0165***	0.0219***	0.0034***	0.0150***
	(0.0062)	(0.0041)	(0.0011)	(0.0042)
$DESTRUCTION_{t-8m}$	0.0015	0.0167***	0.0023*	0.0183*
	(0.0078)	(0.0045)	(0.0012)	(0.0099)
$DESTRUCTION_{t-8.5m}$	0.0149**	0.0161***	0.0045***	0.0173***
	(0.0065)	(0.0035)	(0.0012)	(0.0050)
$DESTRUCTION_{t-9m}$	0.0169**	0.0113***	0.0045***	0.0171***
	(0.0081)	(0.0035)	(0.0009)	(0.0052)

Table 8 (continued)

Banking Variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
$DESTRUCTION_{t-9.5m}$	0.0183***	0.0110**	0.0054***	0.0158***
	(0.0070)	(0.0046)	(0.0011)	(0.0053)
$DESTRUCTION_{t-10m}$	0.0170***	0.0117**	0.0050***	0.0083*
	(0.0061)	(0.0051)	(0.0010)	(0.0046)
$DESTRUCTION_{t-10.5m}$	0.0153***	0.0086**	0.0050***	0.0080*
	(0.0034)	(0.0043)	(0.0010)	(0.0044)
$DESTRUCTION_{t-11m}$	0.0164***	0.0106**	0.0054***	0.0090**
	(0.0031)	(0.0042)	(0.0009)	(0.0038)
$DESTRUCTION_{t-11.5m}$	0.0120***	0.0107**	0.0050***	0.0151*
	(0.0039)	(0.0046)	(0.0009)	(0.0079)
$DESTRUCTION_{t-12m}$	0.0150***	0.0128***	0.0053***	0.0146*
	(0.0027)	(0.0041)	(0.0012)	(0.0087)
Fixed-effects				
Factor (month)	Yes	Yes	Yes	Yes
Factor (year)	Yes	Yes	Yes	Yes
Factor (Location)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,650	1,650	1,650	1,650
R^2	0.97119	0.92888	0.98568	0.96942
Within R^2	0.04509	0.01855	0.01205	0.03089

Heteroskedasticity-robust standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

dummy variables indicating whether a particular branch had been impacted by the first *(STORM1 TREATED)*, second *(STORM2 TREATED)*, or third *(STORM3 TREATED)* storm. The baseline regression from the paper is also included. Furthermore, I introduced two interactions to illustrate whether a branch was affected by the first and second or the first and third storm. Overall, the results from Table 9 do not significantly differ from those in the baseline specification. However, it is noteworthy that the first storm resulted in a decrease in *CAC*, the second storm led to a significant decrease in all variables, and the third storm had a positive impact on *CAC*, *SAV* and *DEP*, whereas it had a negative effect on *CAO*. Furthermore, the interaction terms suggest that the distinct storms had diverse effects on the banking variables.

As previously shown, the first and second storms had the highest estimated wind speeds and destruction. For this reason, I restricted the subsample up to October 1925 and re-estimated the baseline regression displayed in Table 10. Findings demonstrated similarities with those from the baseline regression, and implied that the first two storms initially reduced *CAC*, increased *CAO* and *DEP* over a longer time span, and increased *SAV* roughly nine months after the landfall. Similarly, the magnitude values are less than those in the baseline regression, consistent with the outcomes exhibited in Table 9.

Table 9 Effect of tropical storms on banking variables

Banking variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
Variables				
STORM1_TREATED	−0.2240***	0.0068	−0.0267	−0.1465
	(0.0600)	(0.1001)	(0.1067)	(0.1036)
STORM2_TREATED	−0.2609***	−0.1744***	−0.1176***	−0.1690***
	(0.0384)	(0.0634)	(0.0108)	(0.0639)
STORM3_TREATED	0.2049***	−0.2397***	0.0315***	0.0485*
	(0.0461)	(0.0604)	(0.0120)	(0.0260)
$DESTRUCTION_t$	0.0021	0.0078**	0.0006	0.0040
	(0.0028)	(0.0034)	(0.0042)	(0.0039)
$DESTRUCTION_{t-0.5m}$	0.0082**	0.0135***	0.0027	0.0162***
	(0.0033)	(0.0049)	(0.0028)	(0.0042)
$DESTRUCTION_{t-1m}$	0.0096***	0.0099*	0.0010	0.0167***
	(0.0026)	(0.0055)	(0.0032)	(0.0053)
$DESTRUCTION_{t-1.5m}$	0.0077***	0.0092	-5.04×10^{-5}	0.0143***
	(0.0024)	(0.0060)	(0.0024)	(0.0046)
$DESTRUCTION_{t-2m}$	0.0072***	0.0028	0.0010	0.0140***
	(0.0027)	(0.0091)	(0.0022)	(0.0045)
$DESTRUCTION_{t-2.5m}$	0.0045	0.0074	0.0011	0.0133***
	(0.0046)	(0.0082)	(0.0017)	(0.0039)
$DESTRUCTION_{t-3m}$	0.0018	0.0126***	9.16×10^{-6}	0.0131***
	(0.0053)	(0.0047)	(0.0018)	(0.0038)
$DESTRUCTION_{t-3.5m}$	−0.0026	0.0239***	−0.0007	0.0107**
	(0.0051)	(0.0053)	(0.0021)	(0.0045)
$DESTRUCTION_{t-4m}$	−0.0007	0.0307***	0.0003	0.0126***
	(0.0037)	(0.0041)	(0.0021)	(0.0048)
$DESTRUCTION_{t-4.5m}$	−0.0004	0.0294***	−0.0013	0.0132***
	(0.0059)	(0.0040)	(0.0016)	(0.0048)
$DESTRUCTION_{t-5m}$	0.0022	0.0250***	−0.0020	0.0155***
	(0.0048)	(0.0048)	(0.0016)	(0.0052)
$DESTRUCTION_{t-5.5m}$	−0.0009	0.0275***	−0.0005	0.0132***
	(0.0047)	(0.0043)	(0.0015)	(0.0050)
$DESTRUCTION_{t-6m}$	0.0022	0.0279***	−0.0010	0.0114**
	(0.0040)	(0.0037)	(0.0019)	(0.0057)
$DESTRUCTION_{t-6.5m}$	0.0019	0.0334***	3.33×10^{-6}	0.0100*
	(0.0032)	(0.0106)	(0.0019)	(0.0061)
$DESTRUCTION_{t-7m}$	0.0038	0.0202***	0.0011	0.0104*
	(0.0054)	(0.0038)	(0.0014)	(0.0063)
$DESTRUCTION_{t-7.5m}$	0.0112***	0.0174***	0.0023**	0.0100
	(0.0034)	(0.0031)	(0.0010)	(0.0063)

Table 9 (continued)

Banking variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
$DESTRUCTION_{t-8m}$	0.0040	0.0166***	0.0019	0.0226**
	(0.0081)	(0.0038)	(0.0013)	(0.0097)
$DESTRUCTION_{t-8.5m}$	0.0101***	0.0116***	0.0035***	0.0127*
	(0.0038)	(0.0032)	(0.0010)	(0.0066)
$DESTRUCTION_{t-9m}$	0.0120**	0.0067**	0.0035***	0.0123*
	(0.0051)	(0.0032)	(0.0007)	(0.0064)
STORM1_TREATED x STORM2_TREATED	−0.1284***	−0.0458	0.0743***	−0.2934***
	(0.0452)	(0.0595)	(0.0131)	(0.0704)
STORM1_TREATED x STORM3_TREATED	−0.0620	−0.3673***	0.0390*	−0.0426
	(0.1001)	(0.0630)	(0.0202)	(0.0508)
Fixed-effects				
Factor (month)	Yes	Yes	Yes	Yes
Factor (year)	Yes	Yes	Yes	Yes
Factor (Location)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,650	1,650	1,650	1,650
R^2	0.97372	0.93009	0.98578	0.97118
Within R^2	0.12883	0.03523	0.01857	0.08681

Heteroskedasticity-robust standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

5.4.4 Pre-trends and 1910 population data

In Table 11 I re-estimated the outcomes presented in Table 9 by incorporating six pre-trends that encompassed the three months preceding the storm's landfall. When comparing the results in Tables 9 and 11 it is clear that there were no pre-trends in the variables before the storm hit. Moreover, the findings do not significantly deviate between the two models.

Additionally, I also ran the baseline regression with the 1910 population data, which did not change the destruction index much (as there was not much change in the population), and again did not change the results. I also used the average population per 9.5×9.5 km grid cell in 1920 across all branches, which corresponds to 4845 inhabitants per grid cell.[19] With the average population across all branches I re-estimated the baseline regression so that the population weight is the same across branches. The results of this regression are shown in Table 12 and only the effect size changes. The fall in size may not be surprising since the population in 1910 is less likely to reflect the exposure for our sample period then using the 1920

[19] This corresponds to 54 people per squarekilometer, which is roughly the recent population density of Uruguay.

Table 10 Effect of tropical storms on banking variables (subsample)

Banking variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
Variables				
$DESTRUCTION_{t-0.5m}$	0.0123***	0.0090***	0.0013	0.0116***
	(0.0031)	(0.0030)	(0.0032)	(0.0032)
$DESTRUCTION_{t-0.5m}$	0.0055**	0.0100***	0.0018	0.0107***
	(0.0024)	(0.0033)	(0.0029)	(0.0036)
$DESTRUCTION_{t-1m}$	0.0069*	0.0064*	-7.56×10^{-5}	0.0121**
	(0.0042)	(0.0034)	(0.0032)	(0.0052)
$DESTRUCTION_{t-1.5m}$	0.0055	0.0056	−0.0010	0.0098***
	(0.0051)	(0.0038)	(0.0023)	(0.0037)
$DESTRUCTION_{t-2m}$	0.0049	−0.0005	−0.0001	0.0098**
	(0.0054)	(0.0074)	(0.0022)	(0.0039)
$DESTRUCTION_{t-2.5m}$	0.0022	0.0030	2.49×10^{-5}	0.0089***
	(0.0060)	(0.0070)	(0.0017)	(0.0029)
$DESTRUCTION_{t-3m}$	-3.95×10^{-5}	0.0080**	−0.0010	0.0089***
	(0.0067)	(0.0036)	(0.0018)	(0.0030)
$DESTRUCTION_{t-3.5m}$	−0.0047	0.0193***	−0.0015	0.0067***
	(0.0066)	(0.0062)	(0.0018)	(0.0023)
$DESTRUCTION_{t-4m}$	−0.0031	0.0253***	−0.0004	0.0083***
	(0.0049)	(0.0049)	(0.0021)	(0.0020)
$DESTRUCTION_{t-4.5m}$	−0.0036	0.0242***	−0.0023*	0.0083***
	(0.0067)	(0.0049)	(0.0013)	(0.0020)
$DESTRUCTION_{t-5m}$	−0.0004	0.0207***	−0.0027*	0.0116***
	(0.0052)	(0.0054)	(0.0014)	(0.0019)
$DESTRUCTION_{t-5.5m}$	−0.0034	0.0232***	−0.0012	0.0093***
	(0.0045)	(0.0050)	(0.0014)	(0.0026)
$DESTRUCTION_{t-6m}$	−0.0007	0.0243***	−0.0020	0.0079***
	(0.0054)	(0.0040)	(0.0019)	(0.0024)
$DESTRUCTION_{t-6.5m}$	−0.0010	0.0301***	−0.0007	0.0065**
	(0.0063)	(0.0084)	(0.0019)	(0.0025)
$DESTRUCTION_{t-7m}$	0.0009	0.0171***	0.0003	0.0067***
	(0.0087)	(0.0039)	(0.0015)	(0.0026)
$DESTRUCTION_{t-7.5m}$	0.0089	0.0137***	0.0016	0.0061**
	(0.0062)	(0.0046)	(0.0013)	(0.0028)
$DESTRUCTION_{t-8m}$	−0.0066	0.0095**	-1.41×10^{-5}	0.0105*
	(0.0082)	(0.0039)	(0.0016)	(0.0063)
$DESTRUCTION_{t-8.5m}$	0.0071	0.0084***	0.0024*	0.0084**
	(0.0066)	(0.0025)	(0.0014)	(0.0035)
$DESTRUCTION_{t-9m}$	0.0093	0.0038	0.0027***	0.0081**
	(0.0085)	(0.0025)	(0.0010)	(0.0035)

Table 10 (continued)

Banking variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
Fixed-effects				
Factor (month)	Yes	Yes	Yes	Yes
Factor (year)	Yes	Yes	Yes	Yes
Factor (Location)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,349	1,349	1,349	1,349
R^2	0.97057	0.93821	0.98749	0.97151
Within R^2	0.01358	0.01355	0.00418	0.01076

Heteroskedasticity-robust standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Effect of the first and second tropical storm on the Banking Variables

population, and hence would be introducing some attenuation bias in our damage index.

6 Conclusion

This study explores the role of banks in the aftermath of natural disasters by providing a historical perspective on the impact of tropical storms on clients of the British Caribbean banking system during the 1920s, an era when banks did not grant loans for long-term investments. Natural disasters, such as tropical storms, pose a significant threat to people's livelihood and cause substantial damage to private and public capital like infrastructure, homes, or plantations. After such disasters, individuals often require financial aid to repair damage or sustain themselves in the absence of income, especially if their crops are destroyed. In this context, banks serve as a pivotal institution where clients can save, store, invest money, or obtain loans and advances.

The methodology used in this research involved the creation of a unique dataset that incorporates high-frequency banking data from the 26 branches of the Colonial Bank in the British Caribbean between 1922 and 1927. This data set allowed for a detailed analysis of the bank's operations and their client's behaviour. The study's findings reveal a multifaceted and significant impact of tropical storms on the clients of the Colonial Bank. Tropical storms immediately influenced clients' financial behaviour, which in turn affected the Colonial Bank's balance sheet. Following a storm, clients would typically transfer money from other banks or branches and overdraw their accounts to finance repairs to their homes, plantations, or factories. Colonial Bank, however, was able to attract additional deposits to prevent negative funding shocks. Approximately three months after a tropical storm, net money inflows turned negative, suggesting that clients borrowed and spent more than they initially transferred. Interestingly, around 7.5 months after the disaster,

Table 11 Effect of tropical storms on banking variables (including pre-trends)

Banking variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
Variables				
$DESTRUCTION_{t+3m}$	0.0004	−0.0011	−0.0017	−0.0020
	(0.0033)	(0.0039)	(0.0041)	(0.0029)
$DESTRUCTION_{t+2.5m}$	0.0006	-0.0076^{**}	−0.0001	−0.0029
	(0.0033)	(0.0036)	(0.0049)	(0.0031)
$DESTRUCTION_{t+2m}$	−0.0025	−0.0082	0.0009	−0.0029
	(0.0023)	(0.0051)	(0.0048)	(0.0031)
$DESTRUCTION_{t+1.5m}$	0.0023	0.0043	−0.0002	−0.0032
	(0.0034)	(0.0042)	(0.0041)	(0.0033)
$DESTRUCTION_{t+1m}$	0.0008	0.0021	4.24×10^{-6}	−0.0029
	(0.0020)	(0.0063)	(0.0049)	(0.0034)
$DESTRUCTION_{t+0.5m}$	−0.0009	0.0059	−0.0011	0.0004
	(0.0025)	(0.0050)	(0.0054)	(0.0029)
STORM1_TREATED	-0.2493^{***}	−0.0137	−0.0382	-0.1627^{*}
	(0.0656)	(0.1009)	(0.1043)	(0.0877)
STORM2_TREATED	-0.2580^{***}	-0.1846^{***}	-0.1228^{***}	-0.1739^{***}
	(0.0385)	(0.0646)	(0.0110)	(0.0641)
STORM3_TREATED	0.2096^{**}	-0.1463^{*}	0.0247^{*}	0.0638^{*}
	(0.0930)	(0.0753)	(0.0138)	(0.0361)
WIND	−0.0004	0.0073^{**}	0.0001	0.0021
	(0.0029)	(0.0036)	(0.0041)	(0.0032)
$DESTRUCTION_{t-0.5m}$	0.0065^{**}	0.0139^{***}	0.0025	0.0140^{***}
	(0.0031)	(0.0051)	(0.0028)	(0.0034)
$DESTRUCTION_{t-1m}$	0.0077^{***}	0.0100^{*}	0.0005	0.0144^{***}
	(0.0027)	(0.0053)	(0.0032)	(0.0044)
$DESTRUCTION_{t-1.5m}$	0.0063^{**}	0.0092	−0.0005	0.0122^{***}
	(0.0026)	(0.0059)	(0.0024)	(0.0036)
$DESTRUCTION_{t-2m}$	0.0057^{**}	0.0032	0.0004	0.0122^{***}
	(0.0029)	(0.0091)	(0.0022)	(0.0036)
$DESTRUCTION_{t-2.5m}$	0.0031	0.0067	0.0006	0.0113^{***}
	(0.0046)	(0.0086)	(0.0017)	(0.0030)
$DESTRUCTION_{t-3m}$	0.0008	0.0117^{**}	−0.0004	0.0113^{***}
	(0.0054)	(0.0049)	(0.0017)	(0.0029)
$DESTRUCTION_{t-3.5m}$	−0.0036	0.0236^{***}	−0.0010	0.0092^{***}
	(0.0052)	(0.0054)	(0.0020)	(0.0036)
$DESTRUCTION_{t-4m}$	−0.0020	0.0296^{***}	0.0002	0.0108^{***}
	(0.0037)	(0.0042)	(0.0021)	(0.0038)
$DESTRUCTION_{t-4.5m}$	−0.0025	0.0284^{***}	−0.0017	0.0108^{***}
	(0.0058)	(0.0041)	(0.0015)	(0.0038)

Table 11 (continued)

Banking variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
$DESTRUCTION_{t-5m}$	0.0002	0.0249***	−0.0022	0.0136***
	(0.0047)	(0.0047)	(0.0016)	(0.0047)
$DESTRUCTION_{t-5.5m}$	−0.0028	0.0274***	−0.0007	0.0113***
	(0.0045)	(0.0042)	(0.0015)	(0.0042)
$DESTRUCTION_{t-6m}$	0.0002	0.0278***	−0.0013	0.0096*
	(0.0039)	(0.0038)	(0.0019)	(0.0050)
$DESTRUCTION_{t-6.5m}$	−0.0001	0.0332***	−0.0002	0.0082
	(0.0034)	(0.0107)	(0.0019)	(0.0055)
$DESTRUCTION_{t-7m}$	0.0018	0.0200***	0.0008	0.0084
	(0.0056)	(0.0039)	(0.0014)	(0.0056)
$DESTRUCTION_{t-7.5m}$	0.0093***	0.0174***	0.0021*	0.0082
	(0.0036)	(0.0032)	(0.0011)	(0.0057)
$DESTRUCTION_{t-8m}$	0.0014	0.0166***	0.0017	0.0202**
	(0.0081)	(0.0039)	(0.0014)	(0.0081)
$DESTRUCTION_{t-8.5m}$	0.0080**	0.0117***	0.0032***	0.0108*
	(0.0039)	(0.0033)	(0.0010)	(0.0060)
$DESTRUCTION_{t-9m}$	0.0099*	0.0067**	0.0032***	0.0103*
	(0.0053)	(0.0033)	(0.0007)	(0.0057)
STORM1_TREATED x STORM2_TREATED	−0.1105**	−0.0432	0.0790***	−0.2488***
	(0.0455)	(0.0598)	(0.0128)	(0.0694)
STORM1_TREATED x STORM3_TREATED	−0.1395	−0.3682***	0.0166	−0.0557
	(0.1160)	(0.1200)	(0.0198)	(0.0932)
Fixed-effects				
Factor (month)	Yes	Yes	Yes	Yes
Factor (year)	Yes	Yes	Yes	Yes
Factor (Location)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,514	1,514	1,514	1,514
R^2	0.97497	0.93425	0.98652	0.97271
Within R^2	0.12410	0.02696	0.02000	0.07536

Heteroskedasticity-robust standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

clients significantly increased their savings balances, indicating precautionary savings. The data also indicate that clients preferred to cover storm damage by borrowing money instead of using their deposits or savings. Given that the Colonial Bank was not permitted to offer long-term loans secured by property, damaged collateral did not directly influence the amount of loans granted. Furthermore, although the Colonial Bank did not provide its customers with long-term loans, the results reveal

Table 12 Effect of tropical storms on banking variables: Homogenous Population Weights

Banking variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
Variables				
$DESTRUCTION_t$	0.5620**	0.5519***	0.0354	0.9456***
	(0.2739)	(0.1696)	(0.1282)	(0.1871)
$DESTRUCTION_{t-0.5m}$	0.2836	0.5722***	0.0487	0.8649***
	(0.1920)	(0.1868)	(0.1199)	(0.1836)
$DESTRUCTION_{t-1m}$	0.3845*	0.3880*	−0.0408	0.8678***
	(0.1974)	(0.2041)	(0.1310)	(0.2538)
$DESTRUCTION_{t-1.5m}$	0.4394**	0.3692*	−0.0129	0.7399***
	(0.1971)	(0.2147)	(0.1223)	(0.2059)
$DESTRUCTION_{t-2m}$	0.3613*	0.2927	−0.0321	0.7288***
	(0.2053)	(0.2184)	(0.0881)	(0.2110)
$DESTRUCTION_{t-2.5m}$	0.2920	0.1884	0.0173	0.6569***
	(0.1921)	(0.2821)	(0.0840)	(0.1851)
$DESTRUCTION_{t-3m}$	0.1482	0.2659	−0.0057	0.6910***
	(0.2257)	(0.2695)	(0.0755)	(0.1832)
$DESTRUCTION_{t-3.5m}$	0.1456	0.7539***	−0.0411	0.5878***
	(0.2646)	(0.2171)	(0.0729)	(0.1574)
$DESTRUCTION_{t-4m}$	0.0226	1.022***	−0.0496	0.5891***
	(0.2698)	(0.3125)	(0.0846)	(0.1730)
$DESTRUCTION_{t-4.5m}$	0.0397	1.161***	0.0058	0.6542***
	(0.2277)	(0.2890)	(0.0843)	(0.1580)
$DESTRUCTION_{t-5m}$	0.2000	1.087***	−0.0513	0.7749***
	(0.2741)	(0.2532)	(0.0683)	(0.1486)
$DESTRUCTION_{t-5.5m}$	0.1584	1.115***	−0.0401	0.8638***
	(0.2263)	(0.2678)	(0.0737)	(0.1372)
$DESTRUCTION_{t-6m}$	0.0447	1.186***	−0.0387	0.7050***
	(0.1695)	(0.2168)	(0.0656)	(0.1647)
$DESTRUCTION_{t-6.5m}$	0.3361	0.9440***	−0.0354	0.7090***
	(0.2384)	(0.3239)	(0.0541)	(0.1831)
$DESTRUCTION_{t-7m}$	0.1910	1.411***	0.0431	0.4680**
	(0.3194)	(0.3764)	(0.0494)	(0.2095)
$DESTRUCTION_{t-7.5m}$	0.2508	0.9849***	0.0936*	0.4372*
	(0.3695)	(0.1351)	(0.0499)	(0.2605)
$DESTRUCTION_{t-8m}$	0.2991	0.6182***	0.1180*	0.2759
	(0.3359)	(0.1639)	(0.0676)	(0.3965)
$DESTRUCTION_{t-8.5m}$	0.1591	0.5470***	0.1149**	0.4830
	(0.3167)	(0.1533)	(0.0581)	(0.3554)
$DESTRUCTION_{t-9m}$	0.5752*	0.5317***	0.1415***	0.5451*
	(0.3477)	(0.1769)	(0.0520)	(0.3149)
Fixed-effects				
Factor (month)	Yes	Yes	Yes	Yes

Table 12 (continued)

Banking variable	CAC	CAO	SAV	DEP
Model	(1)	(2)	(3)	(4)
Factor (year)	Yes	Yes	Yes	Yes
Factor (Location)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,659	1,659	1,659	1,659
R^2	0.97018	0.92845	0.98549	0.96927
Within R^2	0.01354	0.01378	0.00250	0.02787

Heteroskedasticity-robust standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

that clients transferred money from other banks or branches or were able to receive loans from financial institutions outside the British West Indies or private individuals. This study underscores the importance of the Colonial Bank in the British Caribbean, highlighting its role in helping clients recover from severe external shocks.

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