The Impact of Climate Change on Cayman's Domestic Financial Institutions: AI-Driven Solutions

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October 2024

Abstract

This research paper explores the intricate relationship between artificial intelligence (AI), climate-related risk (CRR), and financial stability in the context of the Cayman Islands, a prominent international financial centre vulnerable to climate change impacts. As global temperatures rise and extreme weather events become more frequent, the financial sector faces heightened exposure to CRR. By employing a Vector Error Correction Model (VECM), this study examines the relationship between physical CRR (storms and hurricanes) and key financial soundness indicators to better predict and mitigate climate change impacts on domestic banks and insurance companies utilising data over the period 2011-23. The research shows a significant relationship between key bank and insurance variables and CRR, suggesting that AI can improve their modelling and decision-making. The study also suggests that AI can foster sustainable finance initiatives, drive capital towards climate-resilient projects, and promote environmental, social, and governance standards. Moreover, the study calls for collaboration among policymakers, banks, insurance companies, and technology developers to harness AI's potential while addressing associated risks.

JEL Code G21, G22, G32, D80, E44
Keywords climate change, empirical finance, financial stability

1. Introduction

The Cayman Islands, known for its pristine beaches and as an international financial centre, faces unique challenges and opportunities in the context of climate change, financial stability, and the integration of Artificial Intelligence (AI). As a low-lying island territory, the Cayman Islands is particularly vulnerable to the adverse effects of climate change, which includes the increased frequency of extreme weather events. These climate-related changes pose significant risks to the local economy, particularly in sectors such as tourism and finance, which are vital for the islands' economic resilience. Understanding the interplay between these factors is essential for safeguarding the future of the Cayman Islands economy. Financial stability in the Cayman Islands is intricately linked to its ability to adapt to and mitigate the impacts of climate change. The financial services sector, which contributes substantially to the territory's GDP accounting for 45.1 percent in December 2022 (Cefas, 2022), must navigate the emerging risks associated with climate-related disruptions. Specifically, because of their susceptibility to hurricanes in the Caribbean, the Cayman Islands have seen multiple storms that have negatively impacted their economy. A significant amount of the islands' GDP at the time was lost to Hurricane Ivan in 2004, which was one of the most destructive storms ever recorded, with damages estimated to have cost US$3.4 billion (183.0% of 2003 GDP). A protracted recovery process was necessary because the storm severely damaged homes, businesses, and infrastructure. More recently, the resources and tourism-dependent economy of the islands were further strained by Hurricane Paloma in 2008, which resulted in severe damages to Cayman Brac (Cefas, 2022). Furthermore, Hurricane Delta in 2020 also caused damage despite being less severe. Each of these storms draws attention to the challenges faced by the jurisdiction and emphasizes the necessity of strong disaster preparedness and resilient infrastructure to lessen the effects in the future. Investors and institutions are increasingly recognizing the importance of environmental, social, and governance (ESG) criteria in their decision-making processes. As the demand for sustainable investment grows, financial entities in the Cayman Islands are tasked with developing strategies that not only address immediate climate risks but also promote long-term stability and growth in a rapidly changing global landscape.

As the worldwide focus on climate change intensifies, the implications for financial institutions, particularly domestic banks and insurance companies in the Cayman Islands, are becoming increasingly significant. The unique geographical location of the Cayman Islands, coupled with its reliance on tourism and financial services, renders these institutions particularly vulnerable to CRR such as extreme weather events. These risks not only threaten the physical assets of financial institutions but also impact their operational stability, credit risk assessments, and overall profitability. Consequently, the need for effective risk management strategies has never been more critical. In this context, the integration of AI presents a transformative opportunity for banks and insurance companies in the Cayman Islands to enhance their climate risk management frameworks. AI technologies can analyse vast amounts of data, identify patterns, and generate predictive models that help financial institutions better understand and mitigate the potential impacts of CRR. By leveraging AI, these entities can improve their risk assessment processes, optimize their investment portfolios, and develop more resilient insurance products tailored to the evolving climate landscape. Moreover, AI can facilitate real-time monitoring and reporting of climate risks, enabling banks and insurance companies to make informed decisions that align with both regulatory requirements and stakeholder expectations. As climate-related disclosures become increasingly mandated, the ability to harness AI for data analysis and reporting will be essential for maintaining transparency and accountability in the financial sector.

This paper provides an analysis of financial CRR, particularly in the context of local banks and insurance companies given that it has a direct impact on the Cayman Islands economy, and the use of AI in enhancing climate risk management strategies. The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on the relationship between AI and physical CRR as well as AI and financial stability. Section 3 discusses the data and model estimation. In Section 4, the risks and difficulties associated with the interdependence and interaction of AI, financial stability, and climate change are discussed. The conclusion and its implications for the Cayman Islands are finally presented in section 5.

2. Review of Literature

The recognition of climate risk as a significant concern for financial institutions, especially banks and insurance companies, is growing (BIS, 2020). This review of the literature investigates the various ways that banks and insurance companies are affected by CRR, specifically regarding physical risk, and considers how AI can improve risk management capabilities. Physical risks and transition risks are the two main categories into which climate risk falls. According to Chen et al. (2023), natural disasters can pose a physical risk to financial institutions' operations and assets. Conversely, transition risks are linked to the move toward a low-carbon economy and include modifications to regulations, advances in technology, and shifts in consumer preferences (Carney, 2015). As a result of these events, banks and insurance companies' ability to maintain their financial stability is significantly impacted by both kinds of risks (Benali, 2017).

According to Nie (2023), banks are especially susceptible to climate risk through the provision of credit and liquidity to several industries, such as energy, real estate, and agriculture. Studies reveal that banks may experience higher default rates and elevated credit risk if they do not incorporate climate risks into their lending practices (Cardenas 2024). Furthermore, as CRR become more frequent, banks must reevaluate their risk models to properly account for these factors. Global regulatory agencies are starting to understand how critical climate risk is to financial stability. Banks must incorporate climate risk into their risk management frameworks, according to the Basel Committee on Banking Supervision (BCBS 2024). Proactive risk management strategies are even more important, as the European Union has introduced regulations requiring financial institutions to disclose their exposure to climate risks. Because they are responsible for underwriting policies that cover natural disasters, insurance companies are at the forefront of the climate risk landscape. The increasing intensity of climate-related disasters can result in large-scale claims, which would seriously jeopardize insurers' ability to remain solvent (Golnaraghi et al., 2021). Insurance companies need to modify their underwriting procedures to take the evolving risk environment into consideration as the climate crisis worsens.

The financial industry's approaches to risk management could be completely transformed by AI. AI tools can produce insights that improve decision-making processes by analysing large datasets, finding patterns, and producing CRR solutions (Brynjolfsson & McAfee, 2017). Banks and insurance firms can gain a better understanding of potential effects and create more effective risk mitigation plans by integrating AI into climate risk assessments. Predictive analytics is a crucial application of AI in climate risk management. According to Alonso-Robisco et al. (2024), machine learning algorithms could evaluate past data and simulate diverse climate scenarios to predict possible effects on financial performance. Institutions can perform scenario analysis and stress testing with this capability, which gives them important insights into how climate risks might impact their portfolios. AI has the potential to significantly improve the availability and calibre of data linked to climate change. For climate risk assessments, many financial institutions find it difficult to obtain accurate and thorough data (NGFS 2020). AI-driven technologies for data collection and analysis can assist organizations in compiling pertinent information from various sources, enhancing the precision of risk assessments and facilitating better-informed decision-making.

The goal of the Bank for International Settlements' (BIS) Project Gaia is to increase the banking industry's awareness of climate-related financial risks. The goal of Project Gaia is to create methods for evaluating how climate risks affect financial stability by promoting cooperation between central banks, financial regulators, and academic institutions to better be equipped to assess and handle CRR. Projects such as BIS Project Gaia are essential for increasing knowledge of these hazards and encouraging cooperation between interested parties (BIS 2024). By incorporating climate risk factors into pricing models, AI is being used in the insurance industry to improve underwriting procedures. AI algorithms can be used by insurers to evaluate data pertaining to climate exposure and modify premiums as necessary (Sullivan and Gouldson 2017). In addition to improving pricing accuracy, this strategy aids insurers in preserving their financial stability in the face of a rise in climate-related claims. Several banks and insurance companies have begun to implement AI-driven solutions for climate risk management. For instance, some financial institutions are using AI to examine environmental data and satellite imagery to determine how vulnerable their assets are to climate-related disasters (Alonso-Robisco et al 2024). These case studies show how AI can improve risk assessment skills and increase resilience in general to climate change.

From a supervisory perspective, governments worldwide are increasingly recognizing the importance of integrating AI into the regulatory and supervisory frameworks for banks and insurance companies, particularly concerning climate risk (Huw, 2024). AI technologies enable regulators to analyze vast datasets, identify patterns, and predict potential risks associated with climate change. For instance, the European Central Bank (ECB) will use AI-driven models to assess the exposure of financial institutions to CRR (Cipollone 2024). By employing machine learning algorithms, the ECB can evaluate how various climate scenarios might impact the stability of banks and insurance companies, thereby facilitating better-informed decision-making and risk management. In the United States, the Federal Reserve has begun exploring AI tools to enhance its supervisory capabilities regarding climate risk (Doubleday 2023). These tools can analyze financial data and environmental factors to assess the resilience of banks against climate-related shocks (Mullins 2023). For example, the Federal Reserve’s Climate Scenario Analysis framework incorporates AI to model the potential impacts of extreme weather events on the financial sector. This approach allows regulators to proactively identify vulnerabilities and encourage financial institutions to adopt more sustainable practices, ultimately fostering a more resilient financial system in the face of climate change (Huw, 2024). Internationally, various jurisdictions are adopting AI technologies to regulate financial institutions in relation to climate risk. The Bank of England, for instance, has developed the Climate Financial Risk Forum, which leverages AI to create a comprehensive framework for assessing and disclosing climate-related financial risks. This initiative encourages banks and insurers to adopt standardized methodologies for risk assessment, making it easier for regulators to monitor compliance. Additionally, the Australian Prudential Regulation Authority (APRA) has highlighted the importance of AI in transformation of the financial services industry while mitigating its challenges.

In the Caribbean, governments are also beginning to harness AI for regulatory purposes in the banking and insurance sectors, albeit at a nascent stage compared to larger economies. For example, the Central Bank of Barbados is exploring AI-driven analytics to monitor climate risk exposure among financial institutions. By analyzing data related to climate patterns and financial performance, regulators can identify trends that indicate potential risks to the financial sector (WEF 2023). Additionally, the Caribbean Catastrophe Risk Insurance Facility (CCRIF) utilizes AI to model disaster risk and inform insurance pricing, thereby enhancing the resilience of the insurance sector in the face of climate-induced disasters (Phillips, 2021). These efforts highlight the growing recognition of AI’s potential in strengthening regulatory frameworks across different jurisdictions, ensuring that financial institutions are better equipped to manage CRR. According to The Caribbean Community Climate Change Centre (CCCCC) 2021-25 strategic plan, the Centre aims to leverage innovative tools to enhance climate data analysis and predictive modelling (CCCCC 2021), enabling more accurate forecasting of climate impacts across the region. By integrating these tools, the Centre plans to optimize resource management and improve decision-making processes for climate resilience initiatives. The Centre will also utilize the tools to engage communities through tailored communication strategies, raising awareness and promoting climate adaptation practices. Ultimately, these efforts will support the CCCCC's mission to foster sustainable development and enhance the region's capacity to combat climate change.

Though AI has a bright future in mitigating climate risk, there are still obstacles to overcome. Numerous financial institutions are unable to obtain reliable climate-related data, so data availability and quality remain major obstacles (Patnaik et al. 2024). Furthermore, transparency concerns brought on by the intricacy of AI models may make it challenging for interested parties to comprehend the reasoning behind specific judgments. Ethics are another issue that is brought up using AI in climate risk management. To guarantee the responsible deployment of AI technologies, issues concerning accountability, transparency, and bias need to be taken into consideration (Brynjolfsson and McAfee 2017). To preserve the integrity of their risk management procedures, financial institutions need to set up governance frameworks that support moral AI practices. In the future, further study will be required to determine how to incorporate AI into frameworks for managing climate risk. The development of best practices and standardized procedures for applying AI in this situation can be facilitated by cooperative efforts between academic institutions, business, and regulatory agencies. To make sure that these technologies are used appropriately and successfully, it will also be essential to investigate the ethical implications of AI in finance, particularly as it relates to climate risk.

Developing successful climate risk management strategies requires stakeholder engagement. Financial institutions need to work together with investors, regulators, and civil society to comprehend the wider implications of climate risk and create all-encompassing strategies to deal with these issues (NGFS 2020). Involving stakeholders can also improve accountability and transparency in assessments of climate risk. Programs for education and training are becoming more and more necessary as financial institutions use AI technologies for managing climate risk. Financial industry professionals need to have the abilities and know-how required to use AI wisely while being aware of the intricacies of climate risk (Chen et al. 2023). To develop a workforce capable of navigating the changing landscape of climate risk and financial stability, investments in capacity building will be essential. For banks and insurance companies, climate risk presents serious difficulties that call for creative approaches to risk management. AI integration presents viable ways to improve decision-making and climate risk assessment. As financial institutions continue to navigate the complexities of climate risk, embracing AI will be essential for ensuring their resilience and long-term sustainability.

3. Data and Estimation

Our sample includes quarterly data for Cayman's Class A retail banks between 2011-23 and for Cayman's Class A local insurers between 2016-23. Similar to Chen et al. (2023), the financial variables we examine for the banking sector (model 1) includes the capital adequacy ratio (CAR) and non-performing loans (NPLs) and for the insurance sector (model 2), the variables include capital to technical reserves (CTR) and return on assets (ROA) in a similar manner to Benali and Feki (2017). For both sectors, the climate-related variable is natural disasters, specifically storms and hurricanes (SH) (see, e.g., Garcia-Jorcano and Sanchis-Marco, 2024; Walker et al., 2023). We present a description of the variables in appendix table 1.

To estimate the impact of shocks to SH, we employ vector autoregressive estimation, with the options of the standard vector autoregression (VAR) or vector error correction model (VECM). The VAR equation can be established as follows:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_P y_{t-p} + Bx_t + \mu_t \qquad (1)$$

$$t = 1, 2, .. T$$

If y_t is not affected by exogenous time series of d- dimensions $x_t = x_{1t}, x_{2t}, \ldots\ldots x_{dt,}$ the VAR model of formula (1) can be written as follows:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_P y_{t-p} + \mu_t \qquad (2)$$

$$t = 1, 2, .. T$$

With cointegration of formula (2) we can get that

$$\Delta y_t = \prod y_{t-1} + \sum_{i=1}^{k-1} \rho_i \Delta y_{t-i} + \mu_t + \varepsilon_t \qquad (3)$$

Where

$$\prod = y_{t-1} + \sum_{i=1}^{k} A_i - I \qquad (4)$$

$$\rho_i = -\sum_{j=i+1}^{k} A_j$$

If y_t has cointegration relationship, then $\prod y_{t-1} \sim I\ (0)$ and formula (3) can be written as follows.

$$\Delta y_t = \alpha(\beta' Y_{t-1}) + \sum_{i=1}^{k-1} \rho_i \Delta y_{t-i} + \mu_t + \varepsilon_t \qquad (5)$$

Where $\beta' Y_{t-1} = ecm_{t-1}$ is the error correction term, which reflects longterm equilibrium relationships between variables, and the above formula can be written as follows:

$$\Delta y_t = \alpha ecm_{t-1} + \sum_{i=1}^{k-1} \rho_i \Delta y_{t-i} + \mu_t + \varepsilon_t \qquad (6)$$

Formula (6) is the vector error correction model (VECM), in which each equation is an error correction model.

To determine which of these alternatives are appropriate, we begin with stationarity testing using the Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test for stationarity and we display the results in table 1:

Table 1: Stationarity tests

Variables	ADF test			PP test		
	Constant	Trend	No constant	Constant	Trend	No constant
CAR	-0.022	-2.375	0.959	-0.929	-2.988	0.856
NPL	-1.133	-1.668	-1.068	-1.817	-3.460**	-0.834
ROA	-2.205	-2.674	-1.575	-2.701*	-3.062	-1.935*
CTR	-2.561	-2.719	-0.925	-2.424	-2.453	-0.838

Note: The null is the presence of unit roots or non-stationarity while the alternative is that the series is stationary and * and ** denotes statistical significance at 10 and 5 percent significance level, respectively.

The results from the ADF and PP tests confirm that all variables are non-stationary in levels and stationary in first difference (we parsimoniously exclude the results from the first difference stationarity test but they are available upon request). We do not test SH for stationarity since it is a dummy variable. Next, we determine the optimal lag length for the VAR specification is two, using the BIC for both models. Using the Johansen test for cointegration, we confirm the presence of cointegration using both the Trace statistic and the Maximum Eigenvalue approach and we confirm that there is one cointegrating vector for model 1 and model 2 and display the results in Table 2:

Table 2: Cointegration tests

	Trace		Maximum	
		Model 1		
Maximum Rank ®	Restricted trend	Restricted constant	Restricted trend	Restricted constant
0	59.669	53.529	36.949	36.560
1	22.719***	16.969**	13.718*	14.762**
		Model 2		
0	47.440	34.017	34.453	23.528
1	12.987**	10.489	9.033**	6.516**

Note: The null hypothesis is that there are at most or exactly r cointegrating vectors while the alternative is that there are more than r cointegrating vectors and ** denotes the non-rejection of the null hypothesis at 5 percent significance level.

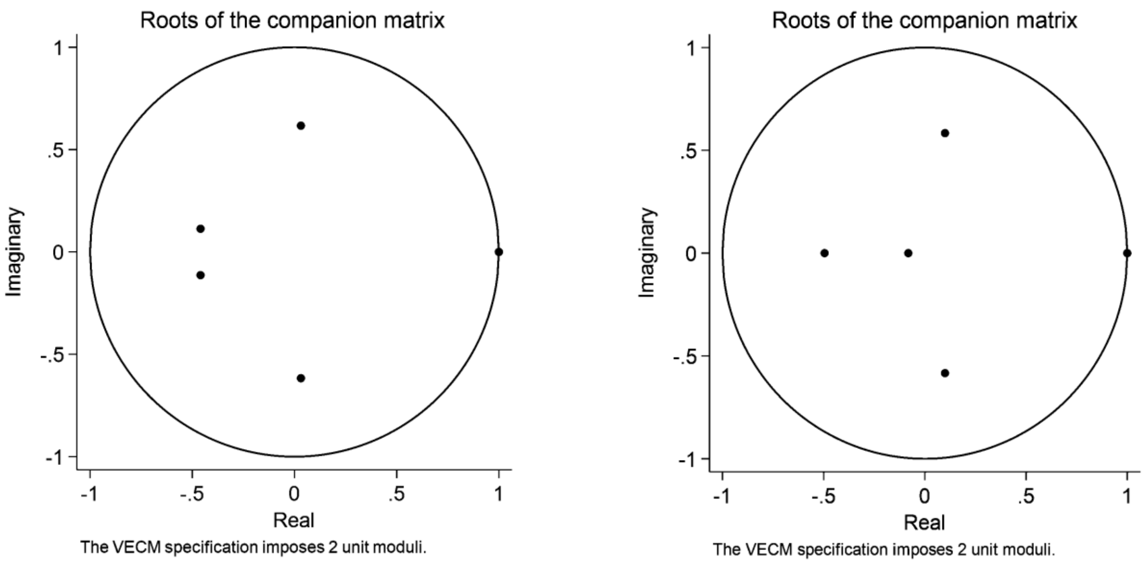
Next, we estimate the VECM using the following specification:

$$\Delta Y_t = \alpha(\beta' Y_{t-1}) + \sum_{i=1}^{k-1} \rho_i \Delta Y_{t-i} + \mu + \varepsilon_t \qquad (1)$$

Where Y is the vector of variables specific to Model 1 and 2, Δ is the first difference operator, α is the long-run adjustment coefficients, β' is the cointegrating vector of long-run relationships, ρ is the matrix of short-run dynamics, μ is the constant and ε is the error term. Before we proceed to interpret the results from the VECM estimation, we examine the models for robustness through stability plots (figure 1) and tests for autocorrelation (table 3) and confirm that both models are indeed robust.

Figure 1: VECM stability plots

Model 1 **Model 2**



Note: The VECM specification imposes two-unit moduli and all other roots of the companion matrix falls within the unit circle indicating that the VECM is stable.

Table 3: Autocorrelation tests

	Model 1	**Model 2**
Lag	Test statistic	Test statistic
1	19.9783***	6.6004*
2	21.051***	4.0238*
3	8.97*	6.0417*
4	9.5065*	6.6924*

Note: The null hypothesis is the absence of autocorrelation and * and *** denotes the non-rejection at the 1 and 10 percent levels of significance respectively.

The error correction term (ECT) or the speed of adjustment coefficient for model 1 are -0.0020 and -0.0133 respectively for the NPL and CAR equations, but they are statistically insignificant. While the negative sign in the ECT suggests the right direction (moving back towards equilibrium), the adjustment process is not significant which implies that deviations from the long-term equilibrium are not being corrected effectively in the short term. This further suggests that short-run dynamics are dominating, and the long-run relationship may be weak. The ECT for model 2 are 0.3046 and -0.0091 respectively for the CTR and ROA equations. The coefficient of the ROA equation is statistically insignificant but the coefficient of the CTR equation is positive and statistically significant at the 5 percent level of significance. The positive value of 0.3046 indicates that the capital-to-technical-reserve ratio is moving away from the long-run equilibrium in the short term, indicating that deviations are not being corrected but rather amplified and insurer's capital structure is not adjusting adequately to the shocks from natural disasters. These results can also be due to the unavoidable and limited time series for model 2.

We then continue with the impulse response functions by ordering the variables based on exogeneity, from most to least exogenous (See, e.g. Love and Zicchino 2006). To this end, we order the variables in model 1 as follows: SH, NPLs, CAR and in model 2 as follows: SH, CTR, ROA.

Results

The results from Model 1 are illustrate in the appendix Figure 1 and it suggests that an orthogonalized shock to SH has a permanent effect on both NPLs and CAR, and the direction of the impact are similar, but the size of the impact is minute. NPLs in Cayman has been historically low over the sample period (averaged two percent) and immediately following a natural disaster shock, there is a fall in NPLs, albeit insignificant. This may seem counterintuitive and contradictory to the findings of Chen et al. (2023) in their analysis of the impact of natural disasters on NPLs in 101 countries, where their study showed significant effects on NPLs both in current and one period lags. However, during the aftermath periods of storms and hurricanes, the banking sector works closely with Cayman residents to offer relief through moratoriums and deferred payment programs with no immediate classification to loans as non-performing. Furthermore, liquidity support may be provided by banks to their borrowers after a disaster, restructuring loans or offering short-term lines of credit to help them through the immediate recovery period. For instance, according to the Cayman Compass (2008), some banks waived mortgage payments and loans for their clients in Cayman Brac and Little Cayman when Hurricane Paloma hit the island in 2008. Also, in many instances, the payout from claims have been used to clear NPLs or pay off mortgages, which can provide some explanation for the fall in NPLs in the aftermath of a storm/hurricane. Cayman Islands Banker's Association (CIBA) Voluntary Banking Code emphasizes a sympathetic and collaborative approach when dealing with customers in financial difficulty, where banks encourage customers to notify the bank early if they are struggling and the bank can work with the customer to develop a tailored plan, with the possibility of alternative repayment arrangements. These modifications can prevent loans from becoming non-performing through reducing the debt burden or extending repayment periods.

Immediately following a natural disaster shock, we acknowledge a marginal decline in the CAR and even though the government and banks will work with borrowers to reduce default, banks may still need to set aside capital for unexpected credit losses in anticipation of potential defaults following a natural disaster. After a disaster, some types of loans may be deemed riskier. The increased perceived risk can also cause these assets to be assigned higher risk weights, reducing the bank's CAR. Our results are consistent with the findings of Gramlich et al. (2023) in their study of approximately ten thousand banks operating in one hundred and forty-nine countries as they find that natural disasters adversely affect bank's capital ratios. However, the results contradict the findings of Nie et al. (2023) who suggests that banks will increase its risk-based capital after a disaster. It is noteworthy that domestic banks in the Cayman Islands typically have CARs of twenty three percent over the review period, which is higher than the Basel requirements and as such may not increase capital positions immediately.

Based on Model 2 (figure 1), after natural disasters such as hurricanes and storms, insurance companies typically experience a sharp increase in claims as policyholders file for damages. As a result, the technical reserves may be depleted as the insurer pays out more claims resulting in the positive response of the CTR to an SH shock for four quarters. In the long run, there is a permanent increase in CTR as technical reserves revert to normal levels and insurers hold more capital commensurate with this exposure.

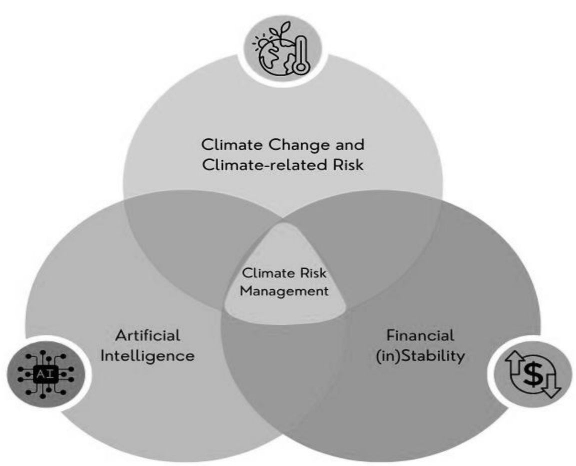
Immediately after a shock to SH, the ROA increases for one period as insurers might initially benefit from pre-existing policies that have already collected premiums thereby generating an increase in net income. However, claims related to the disaster take time to process as losses may have been incurred but not yet reported. During this lag period, insurers continue to hold the premiums as assets, awaiting payments by reinsurers which can temporarily boost ROA. In the short term, ROA could improve as insurers maintain asset levels without recognising significant liabilities. After the initial boost, ROA experiences a significant drop between periods three to five. This can be due to increase claims payouts as insurers start processing and paying out claims for damages caused by the disaster as the surge in claims reduces overall profits, and in some cases, insurers might even operate at a loss.

4. Artificial Intelligence and its Potential Impact on Climate Related Risk management in the context of financial stability for the Cayman Islands

The results of the econometric VECM analysis highlights the significant financial impact of storms and hurricanes on the banking and insurance sectors. After such events technical reserves of insurance companies declines, ROA decreases, CARs of banks weaken, even as NPLs are temporarily reduced through restructuring efforts and through payouts from insurance that go directly to the bank for insured mortgaged properties. To address these challenges, a review of the literature on how new technology driven by AI can benefit and play a crucial role in enhancing the reliance of banks and insurance companies in the Cayman Islands was conducted. This sentiment was echoed by Oliver Junker, Senior Manager of Financial Services Risk Management at EY New York, at Harnessing the Power of GenAI Now, Next and Beyond (2024), which was hosted by CIBA, where she provided a perspective on the potential of GenAI in reshaping the financial services landscape.

The incorporation of AI into risk management procedures has become a game-changer for banks and insurance firms globally as the financial landscape changes. These institutions can identify possible risks more quickly and accurately than they can with traditional methods by using machine learning techniques and sophisticated algorithms to analyse large amounts of data in real-time. In addition to improving predictive analytics and enabling better decision-making, this capability makes it easier to create dynamic risk assessment models that adjust to shifting market conditions. As a result, AI enables financial institutions to maximize their operational efficiency and more successfully reduce risks, which eventually creates a more robust and responsive financial ecosystem.

Figure 2: *The Convergence Nexus: Exploring the Intersections of Climate Change, Artificial Intelligence, and Financial Stability*



The nexus between climate, AI, and financial stability is increasingly critical as the world grapples with the impacts of climate change and seeks sustainable economic growth (figure 2). Climate change poses significant risks to financial systems, affecting asset values, insurance markets, and investment strategies. AI can play a pivotal role in this context by enhancing climate risk assessment, enabling more accurate modeling of climate-related financial risks, and facilitating the development of innovative financial products that promote sustainability. For instance, AI-driven analytics can help financial institutions identify and mitigate exposure to climate risks, while also optimizing investment portfolios towards green technologies and renewable energy. However, the integration of AI in finance also raises concerns about systemic risks, data privacy, and ethical considerations, necessitating a balanced approach to ensure that technological advancements contribute to both climate resilience and financial stability. Thus, fostering collaboration between climate scientists, AI developers, and financial regulators is essential to harness the potential of AI while safeguarding economic integrity in the face of climate challenges.

Globally, as banks and insurance companies struggle with the growing uncertainties posed by climate change, AI is rapidly changing the landscape of risk management in the financial sector One of the primary applications of AI in this context is **the ability to analyse vast amounts of data from diverse sources**. AI algorithms can process and synthesize information from climate models, satellite imagery, weather patterns, and historical data to predict potential climate-related risks. For banks, this means improving credit risk assessments by evaluating the vulnerability of borrowers to climate events, such as floods or droughts, which can impact their ability to repay loans. For insurance companies, AI can enhance underwriting processes by providing more accurate risk assessments for properties and businesses based on their geographic and environmental exposure (Owens et al. 2022). Moreover, AI can facilitate real-time monitoring and early warning systems, enabling banks and insurance firms to respond proactively to emerging climate risks. Machine learning models can be trained to detect patterns and anomalies in environmental data, allowing institutions to identify high-risk areas before a climate event occurs. For instance, insurers can utilize AI to predict the likelihood of severe weather events in specific regions, allowing them to adjust premiums or coverage options accordingly. According to Prajapati (2021) as AXA (motor insurance, Japan) used TensorFlow (AI Programming Library) to consume customer data and predict potential losses, to optimize prices for their insurance policies. The result was a 78.0% accuracy in their predictions. Similarly, banks can monitor the financial health of businesses in climate-sensitive sectors and make informed decisions on lending and investment strategies. This proactive approach not only mitigates potential losses but also fosters a more resilient financial ecosystem.

A significant application of AI in climate risk management is in **scenario analysis and stress testing**. Financial institutions can employ AI-driven simulations to model various climate change scenarios and their potential impacts on portfolios, investments, and overall financial stability. By using advanced algorithms to simulate different climate outcomes such as rising sea levels, extreme weather events, or regulatory changes banks and insurers can better understand the potential vulnerabilities in their operations and develop strategies to mitigate these risks. This capability is particularly important as regulators increasingly require financial institutions to disclose their exposure to climate risks and demonstrate their preparedness for future challenges. In recent years, banks and insurance companies have increasingly turned to AI to address the growing challenges posed by climate-related risks. These institutions face significant exposure to risks associated with extreme weather events, rising sea levels, and shifting climate patterns, which can impact their asset portfolios and underwriting processes. The possibility of biases being reinforced, though, whether because of faulty algorithms or historical data, is still a serious issue that needs to be addressed. Despite these obstacles, financial systems globally moving towards AI-powered methods to more accurately evaluate climate-related risks and opportunities, demonstrating a wider dedication to sustainability and ethical investing. By leveraging AI technologies, financial institutions can enhance their risk assessment capabilities, improve decision-making, and develop more robust strategies for managing climate-related risks. For instance, JPMorgan Chase has implemented AI-driven models that analyze vast datasets, including satellite imagery and climate forecasts, to assess the potential impact of climate change on their loan portfolios and investment strategies. This proactive approach allows them to identify vulnerable assets and adjust their risk exposure accordingly (JPMorgan Chase 2024).

Insurance companies are also utilizing AI to **refine their underwriting processes and enhance their ability to predict and mitigate climate-related risks**. For example, Swiss Re has developed AI algorithms that analyse historical weather data, geographic information, and socio-economic factors to better understand the potential impact of climate change on insured properties. By integrating these insights into their underwriting models, Swiss Re can more accurately price policies and set reserves for potential claims related to climate events. Additionally, AI enables insurers to create more personalized insurance products that reflect the specific risks faced by individual clients, thereby promoting better risk management practices among policyholders (Ladva, 2024). This shift not only helps insurers protect their financial stability but also encourages clients to adopt more resilient practices in the face of climate change. Furthermore, AI is **facilitating the development of innovative financial products aimed at promoting sustainability and climate resilience**. For instance, BNP Paribas has employed AI to create green bonds and sustainability-linked loans that incentivize clients to invest in environmentally friendly projects. By analysing data on a company's carbon footprint and sustainability practices, BNP Paribas can tailor financing options that align with climate goals while managing risk exposure. This integration of AI in the financial sector not only aids in mitigating climate-related risks but also supports the broader transition to a low-carbon economy (BNP Paribas 2021). As banks and insurance companies continue to harness the power of AI, they are better equipped to navigate the complexities of climate change and contribute to a more sustainable future.

Finally, AI can **enhance stakeholder engagement and transparency regarding climate risk management**. Banks and insurance companies can leverage AI-powered tools to generate detailed reports and visualizations that communicate their climate risk exposure and mitigation strategies to investors, regulators, and customers. By providing clearer insights into their risk management practices, these institutions can build trust and credibility with stakeholders who are increasingly concerned about the impacts of climate change. Furthermore, AI can assist in developing tailored financial products that address climate risks, such as green bonds or climate insurance, thus aligning financial services with sustainable development goals and promoting a more resilient economy. Through these multifaceted applications, AI not only strengthens climate risk management but also positions banks and insurance companies in the Cayman Islands as proactive participants in the global response to climate change.

5. Conclusion

The study has illustrated that the Cayman Islands' domestic banks and insurance companies are considerably impacted by physical CRR through the application of the VECM. A comprehensive set of recommendations aimed at protecting the financial stability of banks and insurance companies must be put into effect by policymakers considering the growing physical CRR that the Cayman Islands experience. Within the jurisdiction, regulatory frameworks should be strengthened to mandate that financial institutions evaluate and report physical CRR in their portfolios. Second, domestic banks and insurers should assess the possible long-term effects of climate events on NPLs and the sufficiency of capital reserves by establishing a framework for climate risk stress testing. Furthermore, encouraging investments in green projects and sustainable infrastructure through advantageous financing terms can increase resilience to climate impacts and support these institutions' long-term profitability. Moreover, encouraging cooperation between the financial industry and climate specialists and academia will make it easier to create cutting-edge insurance products that tackle new risks, which will eventually increase insurers' ROA.

Incorporating climate risk considerations into the Cayman Islands' larger economic planning and development strategies will guarantee a comprehensive approach to risk management and promote a robust financial sector that can withstand the difficulties presented by climate change. The Cayman Islands can improve the sustainability and stability of its financial system in the face of changing climate risks by pursuing these initiatives. This is the objective of the Cayman Islands Climate Change Policy for 2024–50 which aims to improve climate risk management by incorporating sustainability into every area of the economy in a thorough and proactive manner. The policy aims to lessen the effects of climate change on vulnerable areas and vital resources by giving priority to resilience-building initiatives like the construction of strong infrastructure and the restoration of natural ecosystems. It also highlights the significance of stakeholder engagement and data-driven decision-making, guaranteeing that local perspectives are heard during the planning phase.

In addition, by leveraging AI with an effective balance for predictive analytics, scenario modelling, and real-time data processing, both banks and insurance companies in the Cayman Islands can enhance their ability to forecast risks, optimize underwriting processes, and develop adaptive strategies that bolster resilience against the financial impacts of climate change. AI and machine learning are two cutting-edge technologies that the Cayman Islands can use to greatly improve their climate risk management plans similar to the experiences of the ECB and the BIS. As such, decision-makers within the Cayman Islands will be better equipped to predict possible effects and create efficient mitigation plans by using machine learning algorithms to assess different climate scenarios. AI-powered solutions can improve supervisory capabilities by offering real-time risk analysis and monitoring related to climate change and guaranteeing that regulatory agencies stay alert and responsive. Moreover, AI can be used by institutions within the Cayman Islands to simulate extreme weather events, improving resource allocation and readiness for such emergencies. To further promote transparency and accountability in the face of climate change, AI can simplify and enhance climate-related disclosures, making it easier and more efficient for companies and organizations to report on their environmental impact and compliance. When combined, these innovations put the Cayman Islands in a proactive position to protect their natural and financial resources while addressing climate challenges.

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Appendix

Table 1: Data

Variables	Period	Source
Domestic Banks		
Non-performing loans (NPLs)	2011-23	CIMA
Capital Adequacy Ratio (CAR)	2011-23	CIMA
Domestic Insurance Companies		
Capital to Technical Reserves (CTTR)	2016-23	CIMA
Return on Assets (ROA)	2016-23	CIMA
Climate-related Variable		
Storms and Hurricane Dummy (SH)	2011-23	National Weather Service Cayman Islands Hazard Management Cayman Islands Cayman Compass- Cayman Storm Centre

Table 2: Summary Statistics

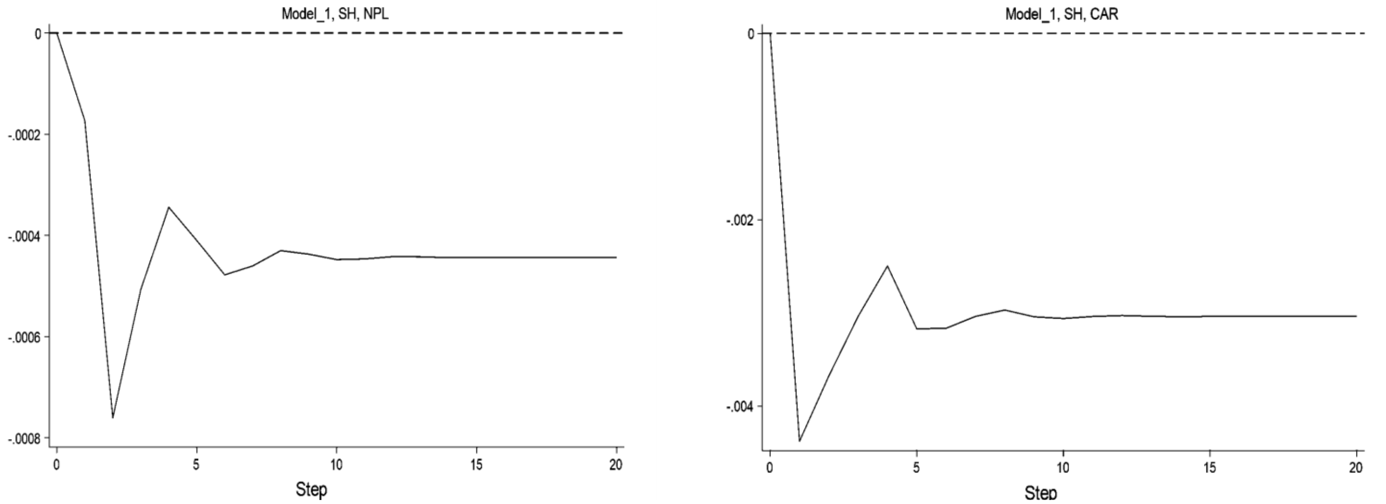
Variable	Observation	Mean	Std.dev	Min	Max
CAR	53	0.23	0.05	0.17	0.31
NPL	53	0.02	0.01	0.01	0.04
CTR	32	0.69	0.26	0.14	1.06
ROA	32	0.01	0.02	-0.02	0.06

Table 3: Correlation

Model -1 Domestic Banks		
	CAR	NPL
CAR	1	-0.67
NPL	-0.67	1
Model - 2 Domestic Insurance (non-life)		
	CTR	ROA
CTR	1	0.37
ROA	0.37	1

Figure 1: Impulse response plots

Model 1



Model 2