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# A Framework for Integrating Extreme Weather Risk, Probability of Default, and Loss Given Default for Residential Mortgage Loans

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**Abstract:** This paper considers a hypothetical case in which a bank wants to build a routine climate stress test exercise on residential mortgage loans. The bank has regularly updated the probability of default (PD) and loss given default (LGD) on each residential mortgage loan under the internal-rating-based (IRB) approach of Basel II/III. Additionally, the bank estimates the stressed PD and stressed LGD associated with a predetermined extreme weather event. Using simulation techniques, this paper shows that the loss of the bank's residential mortgage portfolio can reach a median of around 36% of the portfolio value. This remarkable loss comes from the effects of default correlation and property damage. Banks should pay more attention to such impacts of extreme weather events.

**Keywords:** physical climate risk; residential mortgage loans; probability of default; loss given default; climate stress tests

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## 1. Introduction

Extreme weather events, such as floods, heat waves, cold waves, droughts, and hurricanes, can generate a significant impact on a bank's residential mortgage portfolio. Their impacts can be summarized as follows:

- Damage to property as collateral: They can cause damage to homes and other properties, making it difficult for homeowners to make their mortgage payments to the bank.
- Higher default rate: The bank will encounter higher default rates on mortgage loans in the region concerned. For instance, borrowers may become homeless because of severe damage to their properties and their wealth. Some borrowers may lose their jobs and find it hard to repay loans to the bank.
- Lower property valuation: In addition to direct damage to a property, extreme weather events can lower the market valuation of properties in the region concerned. Other banks may cut their residential mortgage lending for the region. Insurance companies may increase insurance premiums on properties in the region. All these factors lead to lower property values in the region. Then, the bank will encounter higher loan-to-value (LTV) ratios on mortgage loans, higher credit risk estimates on mortgage loans, and higher capital required to support the mortgage lending business.

To deal with climate risks to banks, some bank regulators have taken steps to mitigate the risk of extreme weather events on residential mortgage loans. For example, the bank regulators of the EU, the USA, Canada, Australia, and Hong Kong have guidelines established for lenders to follow when evaluating the risk of default on a loan. These guidelines include requirements for lenders to assess the potential impacts of extreme weather events on a borrower's ability to make payments. The Prudential Banking Authority of the UK encourages banks to consider insurance coverage on residential mortgages against climate catastrophes. This aims to ensure that lenders are adequately protected in an extreme weather event. Both the US and Australian regulators have developed guidelines for lenders to follow when providing relief to borrowers affected by extreme weather events.

These guidelines include requirements for lenders to provide temporary payment relief and additional support for borrowers unable to make mortgage payments due to extreme weather. The Basel Committee makes it clear that banks should consider the possible impacts of extreme weather events on property values associated with collateralized loans and expects bank regulators to develop prudent valuation criteria for their jurisdictions [1].

The impact of extreme weather events on property values is a complex issue that has been the subject of much research in recent years. For instance, the types of climate hazard risks, the resilience of urban development, geolocation, types of buildings, types of economic activities in a region, etc., can affect how a climate hazard damages property values [2]. Banks have an urgent need to improve their property valuation models with multi-criteria techniques [3].

One challenge for bank regulators in managing climate risk on residential mortgage loans in a banking system is the lack of data and information about the potential impacts of extreme weather events. This makes it difficult for regulators to assess the risk of default on a loan and to develop effective strategies to mitigate this risk. In addition, there is a lack of understanding of the potential impacts of extreme weather events on the housing market. This can make it difficult for regulators to evaluate the potential impacts of climate change on the availability of housing and the cost of residential mortgages. Furthermore, there is a lack of agreement among regulators about how to best manage climate risks in the financial system. This can lead to a lack of coordination between regulators, making it difficult to effectively manage climate risk on mortgage loans.

This paper aims to propose a framework to integrate two extreme weather risk measures, namely, stressed PD (probability of default) and stressed LGD (loss given default), into existing credit risk management frameworks used by banks following the internal-rating-based (IRB) approach of Basel II [4]. Since the implementation of Basel II, before 2010, many banks have developed their own IRB systems built for credit risk assessment and capital requirement calculations. These IRB systems continue to be used under Basel III, effective in January 2020. According to Basel Committee rules, the IRB systems produce three major credit risk measures, namely, probability of default (PD), loss given default (LGD), and exposure at default (EAD). Bank regulators convert these three credit risk measures into the capital required for credit risk business. By integrating the proposed extreme weather risk measures, banks can easily conduct climate stress tests on their residential mortgage loans. Meanwhile, bank regulators can easily compare the climate risks of residential mortgage loans from different banks.

Traditional stress tests used by banks aim to evaluate worst-case losses resulting from undesirable economic scenarios. The stress scenarios can be specified by related regulators every year or on an ad hoc basis, associated with a bank's historical experience, based on expert projections, and/or grounded in some statistical confidence levels of market or economic outcomes. Some banks prefer to consider a consistent set of stress scenarios. This enables them to compare the stressed losses of their different business units and perform a trend analysis of stressed losses. The stressed loss results under consistently applied scenarios can be conveniently translated into internal capital allocation and credit pricing. Such methodologies of economic stress tests can be converted to climate stress tests. The goal of the climate stress test is to set an extreme weather scenario and evaluate related losses. Extreme weather events did not happen very often in the past, but they will be more frequent in the future. Bank regulators may occasionally give banks some climate stress scenarios to consider. However, the banks themselves do have an urgent need to routinely evaluate stressed losses due to extreme weather events and determine their business and lending strategies. This is because extreme climate events may arrive with short notice.

This paper considers a hypothetical case in which a bank wants to develop a routine climate stress test exercise for its portfolio of residential mortgage loans. The bank is determined to update the climate stress test results every 6 months, while most bank regulators perform the test at least once a year. This climate stress test exercise is complementary to the ad hoc climate stress tests required by the bank's regulator. It is assumed that the bank routinely updates the PD and LGD of every residential mortgage loan and its related stressed loss arising from a predetermined and hypothetical extreme weather event. With simulation techniques and the assumptions of default correlation, this paper evaluates the stressed loss of the bank's portfolio of residential mortgage loans. The results show that the bank can suffer a loss with a median of around 36% of the portfolio value and with an upper quartile of around 47% of the portfolio value. Such high portfolio losses come from the correlation between defaults and property damage caused by an extreme weather event. The results alert banks when planning their mortgage portfolios in terms of geolocational diversification, insurance against climate catastrophes, mortgage securitization, etc.

This paper will proceed as follows. Section 2 provides a literature review on the impacts of extreme weather on residential mortgage loans, credit risks in extreme weather conditions, and recent actions of bank regulators on climate risk management. Section 3 describes how the hypothetical case study is used in this paper. Section 4 discusses stress test assumptions and results. Section 5 concludes the paper.

## 2. Literature Review

This section summarizes previous studies on the impacts of extreme weather on residential mortgage loans, the credit risk measures on mortgage loans, and recent banking regulation on climate risk management for banks.

### *2.1. Impacts of Extreme Weather Events on Residential Mortgage Loans*

The impacts of extreme weather events on residential mortgage default rates and banks' capital adequacy have become a concern for lenders. Some research [5] notes that lenders charge higher interest rates for mortgages on properties with higher extreme weather risks. This indicates that lenders do consider extreme weather risks in pricing loans, setting lending standards, and selling residential mortgage loans with higher climate risks. However, there is no consensus on how to measure or quantify this risk. This limits the effectiveness of quantitative models of climate risk [6].

Tropical cyclones, for instance, can trigger residential mortgage loan defaults, double residential mortgage default rates, and then weaken banks' capital adequacy [7,8]. This underscores the importance of factoring in climate risk when pricing residential mortgage loans. Insurance companies tend to be more responsive to climate risk in pricing insurance premiums than lenders are in pricing residential mortgage interest rates [6].

In addition, lenders transfer the climate risk to others by securitizing residential mortgage loans with higher climate risks. This practice can mean that lenders transfer the climate risk to mortgage-backed securities in which investors may be unaware of the risks involved [9].

Properties subject to a higher risk of sea-level rise tend to have a deep discount on their sale value. Some highlight that this is because potential buyers are aware of the risks associated with such properties, and they are unwilling to pay the full market value [10]. Previous studies have found that home prices after flooding decline by 25–44% because of the high flooding risk and actual damage to the properties and the regions concerned [11–13]. This can create a challenge for lenders, who may not recover the full amount of the residential mortgage loan if the borrower defaults on the loan. For instance, a residential mortgage loan has its LTV (i.e., loan-to-value) ratio at 70% before a flood, and its property value drops by 40% after the flood. Then, the lender should lose at least 14% of the loan balance.

Furthermore, banks tend to tighten lending standards for a local economy that has recently experienced natural disasters. This is because the risk of residential mortgage defaults tends to increase after natural disasters [14]. This can result in a decline in lending activity, which can negatively impact the local economy.

Overall, banks' CET1 (i.e., Common Equity Tier 1) capital can be weakened by 0.11% to 0.3% due to residential mortgage defaults caused by flooding under various scenarios of global warming [15]. Some studies promote the use of climate VaR (i.e., Value at Risk) to measure the worst-case loss associated with hypothetical climate hazards [16–18]. The

VaR can be used as a basis for setting lending standards, pricing loans, and linking to regulatory capital. While there may be challenges in measuring and quantifying climate risk, lenders can adopt a more proactive approach to mitigate the risks associated with extreme weather events. This may include partnering with insurance companies to develop more effective risk management strategies and exploring innovative financing models that can help borrowers manage climate risk.

### *2.2. Stressed PD and Stressed LGD in Extreme Weather Conditions*

Bank regulators have started requiring banks to estimate the credit risk of loans with the probability of default (PD) and loss given default (LGD) since the implementation of Basel II (Basel Committee, 2006). The PD of loans under Basel II is defined as PD in the next 12 months, which is mostly predicted by borrowers' characteristics, loan types, and other factors. LGD is mostly associated with the collateral type, collateral value, loan-to-value ratio, haircut on liquidating the collateral, and other factors. Macroeconomic environments affect both the PD and LGD. Many studies have documented methods and variables for estimating PD and LGD for residential mortgage loans [19–23].

Bank regulators allow banks to build their own internal models for PD and LGD estimation. Basel III, implemented in 2020, replaced Basel II and has kept PD and LGD as key components of risk management. Most leading banks produce PD and LGD estimates on residential mortgage loans and update these estimates every 3, 6, or 12 months.

In the past, climate risk was mostly ignored by banks because of the rarity of extreme weather events. Economic downturns occur once every 5 to 10 years. Stock market crashes happen once every 10 years. Climate-related catastrophes occur once every 20 to 50 years. Therefore, banks tend to ignore extreme weather events in routine risk management frameworks. However, climate change will surely increase the frequency of extreme weather events. The extreme weather events that bank regulators worry about are, in fact, unprecedented because of rapid climate change in recent years. Hence, it is urgent for banks to build up regular exercises on climate risk management and climate stress testing.

When an extreme weather event takes place, borrowers tend to have their repaying capacity jeopardized and their homes damaged. Their wealth level, the location of their home, the structural type of their home, and other factors can be variables in PD and LGD under extreme-weather stress. The banks themselves may be able to estimate the stressed PD and LGD on their residential mortgage loans using internal judgmental scorecards. The quantitative modeling of the stressed PD and LGD remains challenging because of the limited data available for extreme situations.

### *2.3. Banking Regulation on Climate Risk Management*

In recent years, bank regulation has become increasingly focused on the management of climate-related risks. Banks are now required to assess and manage the potential impacts of climate change on their businesses, as well as the risks posed by their exposure to climate-related events.

The Basel III framework, which was implemented in 2020, requires banks to consider climate-related risks when making lending decisions and managing their portfolios. Banks must consider the potential impacts of climate-related events on their portfolios, as well as the potential impacts of their own activities on the environment. Banks must also develop and implement strategies to manage these climate-related risks.

To effectively manage climate-related risks, banks are expected to understand the potential impacts of climate change on their businesses and the risks posed by their exposure to climate-related events. Banks should also ensure that they are continuously monitoring and assessing their climate-related risks and strategies. By doing so, banks will be able to ensure that they are adequately managing their climate-related risks and that their strategies are aligned with their overall business strategies and objectives. Table 1 shows a list of selected regulatory actions on supervising the climate risk management of banks.

**Table 1.** Regulatory actions on supervising climate risk of banks.

| Time | Bank Regulator | Actions |
|---|---|---|
| April 2019 | Prudential Regulation Authority (UK) | Issued the supervisory statement "Enhancing banks' and insurers' approaches to managing the financial risks from climate change" [24]. |
| May 2020 | European Central Bank | Issued the guideline "Guide on climate-related and environmental risks. Supervisory expectations relating to risk management and disclosure" [25]. |
| December 2020 | Monetary Authority of Singapore | Issued "Guidelines on Environmental Risk Management (Banks)" [26]. |
| October 2021 | Prudential Regulation Authority (UK) | Issued "Climate Change Adaptation Report 2021: Climate-related financial risk management and the role of capital requirements" [27]. |
| November 2021 | Australian Prudential Regulation Authority | Issued the practice guide "Climate Change Financial Risks" [28]. |
| December 2021 | Hong Kong Monetary Authority | Issued the supervisory guidelines "Climate Risk Management" and published its "Pilot climate risk stress test results on selected banks" [29,30]. |
| June 2022 | Basel Committee on Banking Supervision | Published "Principles for the effective management and supervision of climate-related financial risks" [31]. |
| July 2022 | European Central Bank | Issued the results of and comments on "2022 climate risk stress test" [32]. |

## 3. Method of Study

This paper applies a hypothetical case analysis by assuming that a bank aims to conduct a regular climate test. Since the mid-2000s, this bank has developed internal models to estimate PD and LGD on residential mortgage loans. In fact, many sizable banks in advanced economies adopt similar practices in accordance with Basel Committee rules. According to what the Basel Committee expects, these two credit measures are mostly linked to the financial capacity of borrowers, the quality of related collateral, and the leverage ratio when they are applied to residential mortgage loans. Climate risks, including the impacts of severe climate hazards, are commonly excluded. This is because such events did not happen very often in the past, and the PD required is just a probability estimate for the next 12 months.

In order to meet recent requirements for climate stress tests, the bank identifies one extreme weather risk event, namely, a severe hurricane and flooding, and evaluates how this extreme risk event affects the value of its residential mortgage loan portfolio. This event may happen once in the next 5 to 10 years. If the bank has two different extreme weather events, it can apply the analysis repeatedly. Some geolocations are sensitive to hurricanes and flooding, while some are sensitive to heat waves and wildfires.

This paper assumes that the bank has received some information about how the hurricane and flooding event could damage properties. Then, the bank develops its own models for evaluating the stressed PD and stressed LGD on individual residential loans under such a stress scenario. Then, the bank considers correlation default effects and evaluates the total loss of its residential mortgage loan portfolio.

This paper does not challenge the accuracy of the bank's models of stressed PD and stressed LGD. Many scientists and engineers are still exploring new models of physical climate risk because the current issues of climate change are unprecedented. This paper simply outlines a feasible framework for the bank to complete its climate stress test using its own stressed PD and stressed LGD.

There is no right or wrong answer in stress testing because there are a wide range of assumptions for worst-case scenarios. Currently, bank regulators encourage banks to think about worst-case economic scenarios for the next year and require them to prepare for them. In the case of the USA, the Federal Reserve considers one single set of assumptions for worst-case economic scenarios and requires major banks to conduct their analyses using the same set of assumptions. This helps the Federal Reserve identify weaker banks in terms of financial loss or capital adequacy. Assumptions in climate stress tests would have no standard. However, bank regulators do wish banks to develop long-term business strategies for dealing with climate risk.

## 4. Stress Test Assumptions and Results

This section first outlines the economic stress test methodologies developed by the Basel Committee and related bank regulators. Then, it applies a similar approach to conduct climate stress tests and consider possible portfolio losses under the assumptions of default correlation.

Basel Committee rules require banks to estimate PD and stressed LGD under hypothetical or historically observed stress scenarios [33]. Stress testing is an effective tool for banks to evaluate capital adequacy in worst-case situations and may engage a wide range of methodologies. Banks may consider historical stress scenarios, hypothetical stress scenarios, simulation techniques, reverse stress testing approaches, etc. [34–39].

Banks tend to differ in their stress testing methodologies. Their worst-case scenarios can be based on historical experience, expert judgments, regulators' guidelines, statistical models, or a combination of these approaches [40]. Bank regulators generally allow banks to choose their own methodologies but require evidence of using the stress test outputs for business and capital planning, risk appetite setting, risk monitoring, limit setting, regulatory compliance, liquidity contingency funding planning, and recovery planning [40].

Some regulators regularly ask banks to estimate their losses under scenarios specified by the regulators, such as sharp rises in inflation and interest rates, or others. Some regulators set scenarios for stress testing on an ad hoc basis. These scenarios are mostly associated with some of the latest crises or economic threats.

Some banks apply some consistent worst-case scenarios of the financial market and economic conditions. This approach is convenient for banks and allows them to conduct stress testing more frequently, such as every quarter. In general, worst-case scenarios happen rarely. However, a bank's credit risk position can change drastically via loan sales or purchases, but the worst-case scenarios remain the same over the next 24 months. With consistently applied stress scenarios, the bank can compare the internal losses of different units over time, monitor its aggregate loss over time, and incorporate stress test results into the process of internal capital allocation and credit pricing. If the stress scenarios are inconsistent over time, the bank's frontline colleagues will be less likely to accept the inclusion of those stress results into their business planning and performance evaluations. Therefore, some banks apply two sets of stress test exercises: one that is built for regular risk assessment and another one deals with stress scenarios given by their regulators. In this paper, we assume that a bank wants to build a stress test exercise with consistently applied stress scenarios.

### *4.1. Climate Stress Tests*

In 2021–2022, some regulators required banks to undergo climate stress tests. For instance, the Hong Kong Monetary Authority invited a small group of banks to consider the following stress scenarios: a set of greenhouse gas emission assumptions in 2051–2060 and the corresponding estimates of sea-level rise [30]. Then, the banks were asked to evaluate how property-related loans, especially those associated with coastal and low-lying districts, would be affected by typhoons and floods.

The above climate stress test helps banks practice their climate risk assessments but is of little help to banks for near-term climate risk management. Extreme weather events are no longer hypothetical scenarios taking place in 2051–2060. They have happened frequently in both advanced and emerging economies in the last several years. For instance, Spain and Portugal hit a temperature of 45Cs in 2022, while the UK temperature hit 40Cs. Heat waves in Europe caused disastrous wildfires and droughts. In Asia, Pakistan suffered from severe floods in 2022. These affected over one-third of the country's land. China experienced serious floods and droughts in several large cities in 2020–2022. Many rivers in Europe were affected by drought in 2022. These extreme weather events result in economic damage, including electricity shortages, logistic disruptions, property damage, low crop yields, factory shutdowns, public hygiene problems, costs of reconstruction, and others.

### *4.2. Stressed PD and Stressed LGD under a Severe Hurricane and Flooding*

This paper assumes that a bank develops its models to measure stressed PD and stressed LGD under a specified scenario of a severe hurricane and flooding. This extreme weather event is considered by the bank as the most threatening issue to the bank, especially its residential mortgage loans, in the next 5 years.

Both stressed PD and stressed LGD imply that a residential mortgage loan should have a higher PD and a higher LGD under the extreme weather scenario. The bank develops its internal judgmental scorecards to estimate stressed PD and stressed LGD on each residential mortgage loan. It is assumed that the bank applies the following logic to determine its stressed PD and stressed LGD on residential mortgage loans:

- Stressed PD: There are two categories, namely, HIGH RISK and MEDIUM RISK:
    a. The stressed PD (HIGH RISK) group will have a stressed PD equal to 4 times the original PD;
    b. The stressed PD (MEDIUM RISK) group will have a stressed PD equal to 2 times the original PD.
- Stressed LGD: There are two categories: HIGHLY VULNERABLE and VULNERABLE:
    a. The stressed LGD (HIGHLY VULNERABLE) group will have an assumption of 75% damage to the property value;
    b. The stressed LGD (VULNERABLE) group will have an assumption of 25% of the property value.

For the stressed PD, the bank assumes that the severe hurricane and flooding increase the default probability and considers several variables, namely, the financial capacity of a borrower, the LTV of a residential mortgage loan, etc., to categorize stressed PD into two groups: "HIGH RISK" and MEDIUM RISK". For the stressed LGD, the bank considers indicators relating to properties that are vulnerable to the severe hurricane and flooding, such as proximity to hillsides, riversides, and waterfronts, houses in rural areas, properties in low-lying districts (houses, ground-floor apartments, first-floor apartments), etc., to categorize stressed LGD into two groups: "HIGHLY VULNERABLE" and "VULNERABLE". "HIGHLY VULNERABLE" is linked to a property damage ratio of 75%, while "VULNERABLE" is linked to 25%.

In theory, with more historical and external data available, the bank may be able to build equations to link factors to property damages and provide the LTV after the extreme weather event and the stressed LGD on a continuous scale. In practice, with limited information on climate risk, many banks can apply risk categorization with simple assumptions, such as "High-Medium-Low", to classify outcomes after a risk event. Experience in regions with frequent hurricanes does suggest that PD is at least doubled and LGD reaches 100% after a severe hurricane. The above assumptions on stressed PD and stressed LGD are close to those used in real practice.

As mentioned, this paper does not challenge how accurate these models are. In fact, it is hard to obtain suitable historical data to validate the models. It is assumed that the bank updates its regular PD, regular LGD, stressed PD, and stressed LGD on all residential mortgage loans every 6 months.

The flowchart in Figure 1 summarizes how a bank handles credit risk measures, originates loans, and regularly conducts climate stress tests. When a loan is originated, the bank should conduct a credit assessment and prepare both PD and LGD measures under the banking rules of Basel II/III. Meanwhile, with the bank's internal models, the bank can estimate both the stressed PD and stressed LGD relating to its specified extreme weather scenario. Every 6 months, the bank conducts its economic stress tests to evaluate financial losses for the next 12 months and its climate stress tests for its specified extreme weather event in the next 5 years.

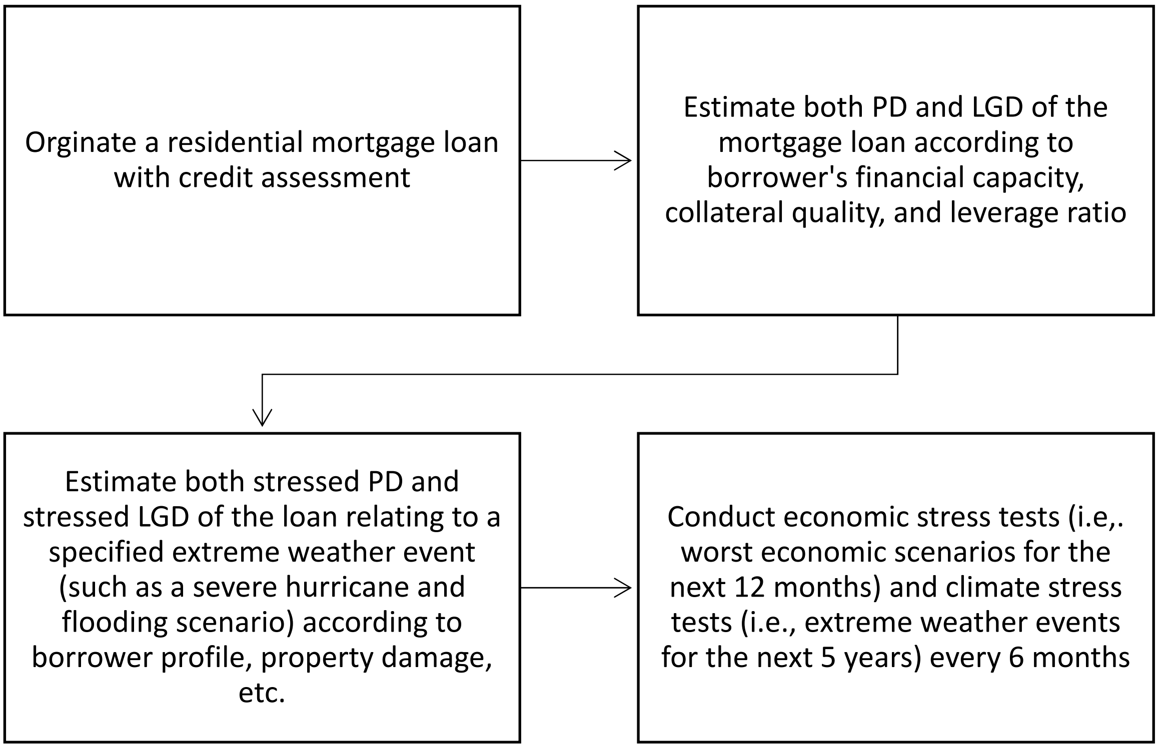


**Figure 1.** Flowchart of risk assessment for a residential mortgage loan and a mortgage loan portfolio.

### *4.3. Lending Preferences of the Bank*

The bank adopts the following practices in its residential mortgage lending:

a. Focus the residential mortgage business on apartments in a large city with property values between USD 500,000 and USD 1,500,000.
b. Set a loan-to-value (LTV) ratio no higher than 70% at the time of loan origination.
c. Engage professional firms to adjust the collateral value once every year according to the latest market environment.
d. Target prime residential mortgage borrowers whose annual PD is between 1% and 4%.
e. Apply a haircut of 30% to the collateral value to estimate LGD, which should have adequately reflected the liquidity cost and administrative and legal costs of foreclosures.

The above lending preferences can vary across different jurisdictions and different banks.

### *4.4. Credit Risk Report of the Residential Mortgage Portfolio*

Banks following the IRB approach of Basel II/III are required to have PD and LGD estimates in place when a loan is originated. These estimates need to be updated at least annually. Some banks update their estimates on a quarterly basis, enabling them to disclose related risk information in their quarterly financial statements. Since a bank may provide many residential mortgage loans, it should rely on some quantitative models to routinely produce PD and LGD estimates. The bank simply updates some input variables and recalculates the PD and LGD estimates.

For easy analysis and illustration, this paper assumes that the bank owns 10 residential mortgage loans only. A similar analysis can be easily applied to over 1000 loans. Table 2, in columns [a] to [g], shows a summary credit report of these 10 loans, including the borrower identification number, outstanding loan balance, updated property value, loan-to-value (LTV) ratio, and both the PD and the LGD in the normal scenario.

**Table 2.** Credit risk analysis using PD, LGD, stressed PD, and stressed LGD.

| | | | Normal Scenario | | | | Extreme Weather Scenario | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Loan [a]** | **Outstanding Loan Balance (USD 000) [b]** | **Property Value (USD 000) [c]** | **LTV [d]** | **PD [e]** | **LGD [f]** | **EL$ [g]** | **Property Damage % [h]** | **Stressed PD [i]** | **Stressed LGD [j]** | **Stressed EL (USD 000) [k]** | **Stressed Loss (USD 000) [l]** |
| 1 | 320 | 500 | 64.0% | 2.50% | 0.0% | 0.0 | 75% | 10.00% | 17.97% | 5.8 | 57.5 |
| 2 | 364 | 700 | 52.0% | 3.90% | 0.0% | 0.0 | 25% | 15.60% | 66.35% | 37.7 | 241.5 |
| 3 | 512 | 800 | 64.0% | 1.00% | 0.0% | 0.0 | 75% | 4.00% | 17.97% | 3.7 | 92.0 |
| 4 | 297 | 900 | 33.0% | 3.50% | 0.0% | 0.0 | 25% | 14.00% | 46.97% | 19.5 | 139.5 |
| 5 | 280 | 1000 | 28.0% | 2.20% | 0.0% | 0.0 | 75% | 8.80% | 0.00% | 0.0 | 0.0 |
| 6 | 385 | 1100 | 35.0% | 2.40% | 0.0% | 0.0 | 25% | 4.80% | 50.00% | 9.2 | 192.5 |
| 7 | 696 | 1200 | 58.0% | 1.80% | 0.0% | 0.0 | 75% | 3.60% | 9.48% | 2.4 | 66.0 |
| 8 | 741 | 1300 | 57.0% | 1.90% | 0.0% | 0.0 | 25% | 3.80% | 69.30% | 19.5 | 513.5 |
| 9 | 882 | 1400 | 63.0% | 1.70% | 0.0% | 0.0 | 75% | 3.40% | 16.67% | 5.0 | 147.0 |
| 10 | 630 | 1500 | 42.0% | 2.20% | 0.0% | 0.0 | 25% | 4.40% | 58.33% | 16.2 | 367.5 |
| Total | 5107 | 10,400 | | | | 0.0 | | | | 118.9 | 1817.0 |
| % Total | | | | | | 0% | | | | 2.33% | 35.58% |

This table summarizes a hypothetical bank's PD, LGD, and loan balances of residential mortgage loans under both normal and extreme weather scenarios. Details of the loans, including credit risk estimates under Basel II/III, are shown in columns [a] to [f]. The stressed PD and stressed LGD in [i] and [j] are based on the bank's credit risk estimates under extreme weather conditions. The stressed PD is set at either 2 × PD or 4 × PD, where PD comes from column [e]. The stressed LGD is based on the property damage ratio (either 25% or 75% in [h]). EL$ in [g] is equal to loan balance × PD × LGD. Total EL$ is zero because all the loans have sufficient collateral margin and thus have zero LGD. The EL$ in [g] is equal to loan balance × stressed PD × stressed LGD. Total stressed expected loss in [k] is a probability-weighted loss amount that assumes no correlation of default. Stressed loss $ in [l] means all defaults happen, and their loss amount is equal to loan balance × stressed LGD. The total stressed loss amount means the loss amount with a 100% correlation of default.

Estimates under the extreme weather scenario include the property damage percentage, the stressed PD, and the stressed LGD. On the basis of the bank's internal risk model, the stressed PD is set at either 4 times or 2 times its PD in the normal scenario. The values are based on the bank's estimates for two types of borrowers: HIGH RISK and MEDIUM RISK.

Stressed LGD is associated with the property damage percentage, which is either 75% (for HIGHLY VULNERABLE) or 25% (for VULNERABLE). These estimates are based on the bank's internal risk model. The expected loss amount (EL$) is the product of the loan balance, PD, and LGD.

The stressed expected loss amount (stressed EL$) is equal to "loan balance × Stressed PD × Stressed LGD". Stressed loss $ is equal to "loan balance × Stressed LGD", which is the loss when extreme weather really takes place.

Table 2, in columns [k] and [l], shows that the stressed EL and stressed loss of the residential mortgage portfolio are USD 118,900 and USD 1,817,000, respectively. Their ratios to the total loan balance are 2.33% and 35.58%, respectively. The latter value is much higher because it is the total portfolio loss when all loans default together. The former value is just the probability-weighted loss amount of the portfolio.

In Table 2, total EL% and total stressed EL% are 0% and 2.33%, respectively. These loss percentages look trivial but may have misled both the banks and their bank regulators. This is because the correlation of loan defaults is ignored. If a 100% correlation with default is assumed, the loss percentage of the residential mortgage portfolio will go up to 35.58%. Correlation can be included in the risk analysis of the mortgage portfolio loss. Although banks may find it hard to accurately predict how loan defaults are correlated, an assumption of zero correlation will understate the risk of the portfolio.

*4.5. Simulation Results with Default Correlation*

Basel II equations for capital requirements include a correlation factor, which is based on the Asymptotic Single-Risk Factor Model [41,42]. This model, widely used by the banking industry [43], assumes an underlying systematic factor ($Z_X$) affecting all asset movements ($Z_Y$). $Z_Y$ and $Z_X$ are correlated in the single-factor model as follows: $Z_Y = b\ Z_X + \sqrt{1-b^2}\ X_{error}$, where $Z_X$ and $Z_{error}$ are random variables with a standard normal distribution. The Basel Committee sets the upper bound of $b$ at 0.489 and its lower bound at 0.346, with the assumption of a negative association between PD and $b$ [41]. A higher PD yields a lower $b$, while a lower PD yields a higher $b$. The Basel Committee argues that the credit risk of large corporations, shown by their lower PD, tends to be more correlated with the systematic factor [41].

We follow the logic of the single-factor model in our simulation analysis and assume that residential mortgage loan defaults tend to be highly correlated under extreme weather events. We simulate $b$ between 0.3 and 0.8 with a uniform distribution. When simulated $Z_Y$ goes below Inverse (Stressed PD), it is counted as a default case. Then, its credit loss is recorded. Inverse (Stressed PD) stands for a critical value of the stressed PD with a standard normal cumulative probability distribution. This inverse of PD, in absolute terms, is also known as distance to default in the banking industry.

In addition to $b$, the bank assumes the confidence intervals of the two groups of stressed PD, namely, HIGH RISK and MEDIUM RISK, and the two groups of property damage %, namely, HIGHLY VULNERABLE and VULNERABLE, for stressed LGD as follows:

- Stressed PD (HIGH RISK): 2 × PD and 6 × PD (NB: the point estimate is 4 × PD in Table 2);
- Stressed PD (MEDIUM RISK): 1 × PD and 4 × PD (NB: the point estimate is 2 × PD in Table 2);
- Property damage % (HIGHLY VULNERABLE): 50% and 100% (NB: the point estimate is 75% in Table 2);
- Property damage % (VULNERABLE): 0% and 50% (NB: the point estimate is 25% in Table 2).

These variables are simulated assuming a uniform distribution and according to their confidence intervals. Table 3 summarizes the variables and parameters in the simulation analysis. Surely, there are questions on why the bank sets assumptions on the confidence intervals and considers a uniform distribution of the input variables. The simulation primarily shows the distribution of outcomes from a set of randomly distributed input variables. The bank considers double the PD as its stressed PD and 6 times the PD as the highest stressed PD in the simulation. For property damage %, the bank has considered 100% as the highest damage percentage for simulation. These upper-bound estimates are prudent enough for a simulation analysis of the residential mortgage portfolio loss. In most cases, the underlying distribution of the input variables is unknown. Thus, a uniform distribution is commonly used due to its simplicity and ease of implementation. It is often used as a starting point for more complex simulations.

The simulated property damage % is then translated to stressed LGD by considering the outstanding loan balance and LTV ratio under stress. The correlation of default is based on the correlation factor $b$ in Table 3, where $b$ ranges between 0.3 and 0.8 with a uniform distribution. One simulation trial produces a set of outcomes for the stressed PD, the stressed LGD, $b$, and the default/nondefault case. Then, the total portfolio loss amounts of this trial are recorded. The distribution of the loss amounts and loss percentages after 10,000 trials of simulation are summarized in Table 4.

Table 4 shows a median portfolio loss percentage of 36.77%, which is close to the total stressed loss percentage of 35.58% in Table 2. The latter percentage assumes a 100% correlation, while the former one assumes a high correlation (not 100%), together with potentially higher stressed PD and higher stressed LGD. The Top 1% and Bottom 1% loss percentages are 63.61% and 11.25%, respectively. They are much higher than the total EL% (i.e., 0%) and the total stressed EL% (i.e., 2.33%) in Table 2. The total EL% and total stressed

EL% in Table 2 may easily understate the risk of the residential mortgage portfolio because of the lack of consideration of default correlation. The portfolio loss % values in Table 4, from Top 1% to Median, are all higher than the total stressed loss of 35.58% in Table 2. This is because this simulation has set higher upper bounds on the stressed PD for both HIGH-RISK and MEDIUM-RISK groups and higher upper bounds on the stressed LGD for both HIGHLY VULNERABLE and VULNERABLE groups.

**Table 3.** Variables and parameters for simulation analysis.

| Parameter or Variable | Category | Confidence Interval | |
|---|---|---|---|
| | | Lower Bound | Upper Bound |
| Stressed PD | HIGH RISK | PD × 2 | PD × 6 |
| | MEDIUM RISK | PD × 1 | PD × 4 |
| Property damage % | HIGHLY VULNERABLE | 50% | 100% |
| | VULNERABLE | 0% | 50% |
| Correlation factor (b) | | 0.3 | 0.8 |

The simulation is based on simulated outcomes for stressed PD and property damage %, which follow a uniform distribution according to their confidence intervals. The PD in the table is the PD under a normal scenario in Table 2. Correlation is based on $b$ in the equation $Z_Y = b\, Z_X + \sqrt{1 - b^2}\, X_{error}$, where $Z_Y$, $Z_X$, and $X_{error}$ are variables with a standard normal distribution.

**Table 4.** Simulated outcomes of the residential mortgage portfolio.

| | Portfolio Loss (USD 000) | Portfolio Loss% |
|---|---|---|
| Top 1% | 3248.5 | 63.61% |
| Top 5% | 2969.2 | 58.14% |
| Top 10% | 2764.1 | 54.12% |
| Top 25% | 2358.1 | 46.17% |
| Median | 1878.0 | 36.77% |
| Bottom 25% | 1358.5 | 26.60% |
| Bottom 10% | 959.3 | 18.78% |
| Bottom 5% | 774.5 | 15.17% |
| Bottom 1% | 574.4 | 11.25% |

This table summarizes portfolio loss amounts of 10,000 simulation trails based on the random variables and parameters in Table 3. Portfolio loss % is the portfolio loss amount divided by the total loan balance in Table 2.

Extreme weather events normally affect all buildings in a region, make defaults correlated, generate huge losses for banks, and increase the default probability. Bank regulators should thus pay more attention to the correlation between default and resulting portfolio loss amounts associated with extreme weather events. Banks should prepare capital to deal with this stressful loss situation.

When extreme weather happens to a city, all buildings in the city will be affected. This means that a community bank in a city with residential mortgage loans mostly provided to its citizens tends to have a higher correlation of mortgage defaults. Global banks and transregional banks with geographically diversified residential mortgage portfolios tend to have a lower correlation of mortgage defaults.

## 5. Summary and Discussion

This paper has discussed how stressed PD and stressed LGD under an extreme weather event affect the residential mortgage portfolio loss. Banks can easily estimate these two indicators with judgmental scorecards by considering the borrower's wealth level, LTV, location of the property, the structure of the property, etc. These two risk estimates can be easily integrated with the PD and LGD, which have been actively used by banks under Basel II/III for credit risk analysis. The expected loss under normal conditions, the stressed expected loss under extreme weather conditions, and the stressed loss under extreme weather conditions can provide banks with insights on the distribution of extreme weather risk.

This paper has also applied a simulation approach by assuming a positive default correlation. The simulation results suggest much higher loss amounts than the expected loss and expected stressed loss. Under default correlation, the portfolio loss can reach a median of 36% and an upper quartile of 47%. Extreme weather events surely result in a positive default correlation. Banks and bank regulators should pay more attention to this correlation effect on the residential mortgage portfolio loss.

### *5.1. Contributions of the Paper*

Bank regulators from advanced economies have started requiring banks to conduct stress tests since 2021. Some regulators determine a set of ad hoc climate scenarios and request their supervised bank to evaluate possible outcomes. Basel Committee rules generally expect banks to build their own climate-related stress test programs. Residential mortgage loans, conventionally counted by banks as safe assets, tend to account for over 30% of a bank's assets. These loans can become risky when extreme weather events become more frequent in the coming years.

This paper has proposed a framework for a bank to evaluate the extreme weather risk of the bank's residential mortgage portfolio. It helps the bank monitor the possible financial loss of its residential mortgage loan portfolio over time. The key in this framework is two risk measures under stress, namely, stressed PD and stressed LGD, associated with a predetermined extreme weather event. These stressed PD and LGD estimates come from the bank's internal judgmental/scoring models of related factors when a residential mortgage loan is originated.

With the stressed PD and stressed LGD, the bank can gain the following advantages:

- The bank can consistently update these stressed PD and LGD estimates and evaluate its extreme weather risk on individual loans and on the whole portfolio over time.
- It can compare the stressed losses of different business units and explore possible business adjustments, such as geolocation diversification, loan sales, mortgage securitization, climate hazard insurance, etc.
- With the proposed framework, which consistently applies the stressed PD and stressed LGD, the bank can conveniently incorporate the expected loss amount associated with extreme weather events into its business planning and risk management for the next several years.

### *5.2. Limitations of the Paper*

This paper has simply assumed one set of stressed PD and stressed LGD regardless of the types of extreme weather. It is true that drought, heat waves, cold waves, hurricanes, etc., could lead to different degrees of loss. If data are available, a bank can estimate the stressed PD and stressed LGD associated with different types of extreme weather. If data are limited, the bank can focus on one or two types of extreme weather with a high likelihood of occurrence in a region.

This paper has assumed that bank analysts are able to estimate the stressed PD and the stressed LGD associated with extreme weather. In reality, this task can be challenging for them. What is certain is that the credit risk in extreme weather conditions should be higher than the credit risk in normal conditions.

Also, this paper has applied a simulation analysis with the assumption of a uniform distribution for all the input variables and parameters. With more data on extreme weather events and their actual impacts, banks may fine-tune the assumptions.

It is true that there are limited historical data for the quantitative risk analysis associated with extreme weather events. However, a risk assessment may start with expert judgments or judgmental scorecards developed by related experts. This judgmental approach was popular in bond rating and bank lending many decades ago. With more data available in the future, a bank can gradually calibrate or adjust its judgmental risk assessment on extreme weather risk.

### *5.3. Credit Risk Management with Extreme Weather Risk Measures*

With the stressed PD, stressed LGD, stressed expected loss, and stressed loss, a bank can perform risk management as follows:

- Risk limit setting: The bank can set credit exposure limits according to estimated loss amounts. The bank should reduce credit exposures for regions with remarkably high loss amounts.
- Risk-based pricing: The bank may have considered PD, LGD, and EL (i.e., PD $\times$ LGD) in residential mortgage loan pricing. In general, risk pricing should be applied to all loans. With the extreme risk measures, the bank can include a percentage of the stressed expected loss and stressed loss into loan pricing for residential mortgages.
- Capital reserve for stressed conditions: A bank's capital aims to absorb losses in stressed conditions. The bank can estimate the portfolio loss under extreme weather conditions and prepare capital to absorb at least some of the stressed loss amount. Estimation should include some level of default correlation.
- Hedging with insurance: The bank may require a residential mortgage borrower to buy weather-related catastrophe insurance if a related property has high extreme weather risk measures.
- Residential mortgage securitization: To reduce credit risk, the bank can sell its residential mortgage loans via securitization. Those residential mortgage loans with high extreme weather risk should be sold first to mitigate the bank's risk exposure [44].
- Geolocational diversification: One effective way to manage extreme weather risk is diversification. On the basis of internal climate-related credit exposure limits, the bank can include residential mortgage loans from different cities and countries in its portfolio.

### *5.4. Predicting Extreme Weather Events*

This paper does not address the issue of how to effectively predict extreme weather events. This is because bank risk analysts do not have the necessary ability to carry out this task and do rely on support from scientists and meteorologists of universities or governmental institutions.

At this stage, many climate models still have challenges in making accurate predictions [18]. Banks may prefer climate models that can predict these events for the next 12 months and thus manage their loan portfolios in advance. While climate scientists and meteorologists have made significant advancements in predicting climate hazards, predicting such events with certainty for the next 12 months is still a challenging task. Most climate models can only predict these events 2 to 4 weeks before they occur [45], which may not be enough time for banks to adjust their loan portfolios.

Most quantitative models are built with historical data. However, scientific observations suggest that climatic extremes may have changed in the past [46]. Hence, traditional models may easily supply misleading predictions. One thing that scientists are certain about is the increased frequency of extreme weather events [47].

### *5.5. Applications to Residential Mortgage Loans in Different Cities and Countries*

This paper simply assumes that the bank in the case study considers one predetermined extreme weather event and estimates the related stressed PD and stressed LGD. This approach is suitable for analyzing the climate risk of residential mortgage loans in a city because all these loans tend to be vulnerable to the same climate risk. If a global bank has residential mortgage loans in different cities and countries, it should group them by region. Each region corresponds to a specified extreme weather event and develops its equations or categorization of stressed PD and stressed LGD. Some regions may be vulnerable to wildfire risk caused by heat waves. Some may be vulnerable to flooding risk caused by hurricanes.

### 5.6. Applications to Other Bank Loans

Can stressed PD and stressed LGD be applied to other bank loans? These two extreme weather risk measures are highly linked to geolocations and can be easily applied to residential mortgage loans. They may be applicable to small business loans, commercial mortgage loans, and infrastructure project loans because their borrowers' income-generating activities are mostly concentrated on their registered geolocations. Loans to large corporations are different because multinational corporations can run globally and deal with customers and suppliers in many different geolocations. Therefore, the framework of this paper is inapplicable to these large corporations.

### 5.7. Final Advice

This paper focuses on the physical risk of residential mortgage loans, which tend to be geolocational. Banks, other residential mortgage lenders, MBS (i.e., mortgage-backed security) investors, and insurance companies underwriting catastrophe insurance all expose themselves to this risk. Will it be possible for the capital market to develop weather derivatives, such as futures and options, to hedge against extreme weather risk? Climate derivatives help various parties to manage their climate risk effectively [25,48]. Currently, the USA market supplies a few weather derivatives, but there are no relevant derivative contracts in Europe, Asia, or other markets. Weather derivatives as financial instruments aim to link payoffs to specified extreme weather outcomes, such as extremely hot temperatures, extremely cold temperatures, extremely high rainfall, extremely low rainfall, etc. These weather derivatives help financial firms, property owners, agri-food companies, investors, etc., to hedge against their losses associated with extreme weather risk. Sizable insurance companies and banks should be willing to serve as dealers and market makers of these derivatives.

In addition, bank regulators in different countries should encourage banks to securitize their residential mortgage loans in the global capital market. This helps banks reduce the extreme weather risk of their residential mortgages. Surely, some geolocations tend to have more frequent events of extreme weather. If MBSs (i.e., mortgage-backed securities) are correctly priced, those associated with a high frequency of extreme weather events should have lower prices. The MBS market will benefit both mortgage loan sellers and MBS buyers. Mortgage loan sellers can offload their risky loans and invest in other assets, while MBS buyers can build a geographically diversified mortgage portfolio.

Extreme weather will surely increase in frequency and is unavoidable. Financial sectors should find some ways to let this weather risk be transferred and shared globally. Weather derivatives and mortgage securitization can be workable solutions.

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## References

1. BCBS. Frequently Asked Questions on Climate-Related Financial Risks. Basel Committee on Banking Supervision. 2022. Available online: https://www.bis.org/bcbs/publ/d543.pdf (accessed on 15 March 2023).
2. Anelli, D.; Tajani, F.; Ranieri, R. Urban resilience against natural disasters: Mapping the risk with an innovative indicators-based assessment approach. *J. Clean. Prod.* **2022**, *371*, 133496. [CrossRef]

3. Locurcio, M.; Tajani, F.; Morano, P.; Anelli, D.; Manganelli, B. Credit Risk Management of Property Investments through Multi-Criteria Indicators. *Risks* **2021**, *9*, 106. [CrossRef]
4. BCBS. International Convergence of Capital Measurement and Capital Standards: A Revised Framework Comprehensive Version. Basel Committee of Banking Supervision. 2006. Available online: https://www.bis.org/publ/bcbs128.pdf (accessed on 15 March 2023).
5. Nguyen, D.D.; Ongena, S.; Qi, S.; Sila, V. Climate Change Risk and the Cost of Mortgage Credit. *Rev. Financ.* **2022**, *26*, 1509–1549. [CrossRef]
6. Dennis, B.N. *Climate Change and Financial Policy: A Literature Review*; Finance and Economics Discussion Series 2022-048; Board of Governors of the Federal Reserve System: Washington, DC, USA, 2022. Available online: https://doi.org/10.17016/FEDS.2022.048 (accessed on 15 March 2023).
7. Calabrese, R.; Dombrowski, T.; Mandel, A.; Kelley, P.R.; Zanin, L. Impacts of Extreme Weather Events on Mortgage Risks and Their Evolution under Climate Change: A Case Study on Florida. 2021. Available online: https://ssrn.com/abstract=3929927 (accessed on 15 March 2023).
8. Kousky, C.; Palim, M.; Pan, Y. Flood Damage and Mortgage Credit Risk: A Case Study of Hurricane Harvey. *J. Hous. Res.* **2020**, *29*, S86–S120. Available online: https://www.tandfonline.com/doi/epub/10.1080/10527001.2020.1840131?needAccess=true (accessed on 15 March 2023). [CrossRef]
9. Keenan, J.M.; Bradt, J.T. Underwaterwriting: From theory to empiricism in regional mortgage markets in the U.S. *Clim. Chang.* **2020**, *162*, 2043–2067. [CrossRef]
10. Keys, B.J.; Mulder, P. Housing Markets, Mortgage Lending, and Sea Level Rise. National Bureau of Economic Research, Working Paper 27930. 2020. Available online: http://www.nber.org/papers/w27930 (accessed on 15 March 2023).
11. Atreya, A.; Ferreira, S. Seeing is Believing? Evidence from Property Prices in Inundated Areas. *Risk Anal.* **2015**, *35*, 828–848. [CrossRef]
12. Atreya, A.; Ferreira, S.; Kriesel, W. Forgetting the Flood? An Analysis of the Flood Risk Discount Over Time. *Land Econ.* **2013**, *89*, 577–596. [CrossRef]
13. Chandra-Putra, H.; Andrews, C.J. An Integrated Model of Real Estate Market Responses to Coastal Flooding. *J. Ind. Ecol.* **2020**, *24*, 424–435. [CrossRef]
14. Duanmu, J.; Li, Y.; Lin, M.; Tahsin, S. Natural Disaster Risk and Residential Mortgage Lending Standards. *J. Real Estate Res.* **2022**, *44*, 106–130. [CrossRef]
15. Bikakis, T. Climate Change, Flood Risk and Mortgages in the UK: A Scenario Analysis. *New Sch. Econ. Rev.* **2020**, *10*, 7–11. Available online: https://nsereview.org/index.php/NSER/article/view/45 (accessed on 15 March 2023).
16. Battiston, S.; Mandel, A.; Monasterolo, I.; Schütze, F.; Visentin, G. A climate stress-test of the financial system. *Nat. Clim. Chang.* **2017**, *7*, 283–288. [CrossRef]
17. Simon, D.; Alex, B.; Charlie, D.; Philip, G. 'Climate value at risk' of global financial assets. *Nat. Clim. Chang.* **2016**, *6*, 676–679.
18. Sillmann, J.; Thorarinsdottir, T.L.; Keenlyside, N.S.; Schaller, N.; Alexander, L.V.; Hegerl, G.C.; Seneviratne, S.I.; Vautard, R.; Zhang, X.; Zwiers, F.W. Understanding, modeling and predicting weather and climate extremes: Challenges and opportunities. *Weather. Clim. Extrem.* **2017**, *18*, 65–74. [CrossRef]
19. Altman, E.I. Default Recovery Rates and LGD in Credit Risk Modelling and Practice: An Updated Review of the Literature and Empirical Evidence. In *Advances in Credit Risk Modelling and Corporate Bankruptcy Prediction*; Cambridge University Press: Cambridge, UK, 2008.
20. Korteweg, A.; Sorensen, M. Estimating Loan-To-Value Distributions. *Real Estate Econ. Am. Real Estate Urban Econ. Assoc.* **2016**, *44*, 41–86. [CrossRef]
21. Leow, M.; Mues, C. Predicting loss given default (LGD) for residential mortgage loans: A two-stage model and empirical evidence for UK bank data. *Int. J. Forecast.* **2012**, *28*, 183–195. [CrossRef]
22. Titman, S.; Tompaidis, S.; Tsyplakov, S. Determinants of Credit Spreads in Commercial Mortgages. *Real Estate Econ.* **2005**, *33*, 711–738. [CrossRef]
23. Tsai, M.S.; Liao, S.; Chiang, S. Analyzing yield, duration and convexity of mortgage loans under prepayment and default risks. *J. Hous. Econ.* **2009**, *18*, 92–103. [CrossRef]
24. PRA. Enhancing Banks' and Insurers' Approaches to Managing the Financial Risks from Climate Change. Supervisory Statement SS3/19. Prudential Regulation Authority (UK). 2019. Available online: https://www.bankofengland.co.uk/-/media/boe/files/prudential-regulation/supervisory-statement/2019/ss319 (accessed on 15 March 2023).
25. ECB. Guide on Climate-Related and Environmental Risks. Supervisory Expectations Relating to Risk Management and Disclosure. European Central Bank. 2020. Available online: https://www.bankingsupervision.europa.eu/legalframework/publiccons/pdf/climate-related_risks/ssm.202005_draft_guide_on_climate-related_and_environmental_risks.en.pdf (accessed on 15 March 2023).
26. MAS. Guidelines on Environmental Risk Management (Banks). Monetary Authority of Singapore. 2020. Available online: https://www.mas.gov.sg/-/media/MAS/Regulations-and-Financial-Stability/Regulations-Guidance-and-Licensing/Commercial-Banks/Regulations-Guidance-and-Licensing/Guidelines/Guidelines-on-Environmental-Risk{-}{-}-Banks/Guidelines-on-Environmental-Risk-Management-for-Banks.pdf (accessed on 15 March 2023).
27. PRA. Climate Change Adaptation Report 2021: Climate-Related Financial Risk Management and the Role of Capital Requirements. Prudential Regulation Authority (UK). 2021. Available online: https://www.bankofengland.co.uk/-/media/boe/files/prudential-regulation/publication/2021/october/climate-change-adaptation-report-2021.pdf (accessed on 15 March 2023).

28. APRA. Climate Risk Management. Prudential Practice Guide 229. Australian Prudential Regulation Authority. 2021. Available online: https://www.apra.gov.au/sites/default/files/2021-11/Final%20Prudential%20Practice%20Guide%20CPG%20229%20Climate%20Change%20Financial%20Risks.pdf (accessed on 15 March 2023).
29. HKMA. Climate Risk Management. Supervisory Manual GS-1. Hong Kong Monetary Authority. 2021. Available online: https://www.hkma.gov.hk/media/eng/doc/key-functions/banking-stability/supervisory-policy-manual/GS-1.pdf (accessed on 15 March 2023).
30. HKMA. Pilot Banking Sector Climate Risk Stress Test. Hong Kong Monetary Authority. 2021. Available online: https://www.hkma.gov.hk/media/eng/doc/key-functions/banking-stability/Pilot_banking_sector_climate_risk_stress_test.pdf (accessed on 15 March 2023).
31. BCBS. Principles for the Effective Management and Supervision of Climate-Related Financial Risks. Basel Committee on Banking Supervision. 2022. Available online: https://www.bis.org/bcbs/publ/d532.pdf (accessed on 15 March 2023).
32. ECB. 2022 Climate Risk Stress Test. European Central Bank. 2022. Available online: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.climate_stress_test_report.20220708~2e3cc0999f.en.pdf (accessed on 15 March 2023).
33. BCBS. Stress Testing Principles. Basel Committee on Banking Supervision. 2018. Available online: https://www.bis.org/bcbs/publ/d450.pdf (accessed on 15 March 2023).
34. End, J.W. Liquidity Stress-Tester: A Model for Stress-testing Banks' Liquidity Risk. *CESifo Econ. Stud.* **2010**, *56*, 38–69.
35. Kapinos, P.S.; Mitnik, O.A. A Top-down Approach to Stress-testing Banks. *J. Financ. Serv. Res.* **2015**, *49*, 229–264. [CrossRef]
36. Peura, S. Simulation-Based Stress Testing of Banks' Regulatory Capital Adequacy. Bank of Finland Research Discussion Paper No. 4/2003. 2003. Available online: https://ssrn.com/abstract=3018089 (accessed on 15 March 2023).
37. Quagliariello, M. (Ed.) *Stress Testing the Banking System: Methodologies and Applications*; Cambridge University Press: Cambridge, UK, 2009.
38. Schuermann, T. Stress Testing Banks. Risk Management & Analysis in Financial Institutions. 2013. Available online: http://econ.queensu.ca/faculty/milne/872/Schuermann,%20Stress%20Testing%20Banks,%20Apr,%202012.pdf (accessed on 15 March 2023).
39. Wong, M.C.; Lam, Y. Macro stress tests and history-based stressed PD: The case of Hong Kong. *J. Financ. Regul. Compliance* **2008**, *16*, 251–260. [CrossRef]
40. BCBS. Supervisory and Bank Stress Testing: Range of Practices. Basel Committee on Banking Supervision. 2017. Available online: https://www.bis.org/bcbs/publ/d427.pdf (accessed on 15 March 2023).
41. BCBS. An Explanatory Note on the Basel II IRB Risk Weight Functions. Basel Committee for Banking Supervision. 2005. Available online: https://www.bis.org/bcbs/irbriskweight.pdf (accessed on 15 March 2023).
42. Vasicek, O. Loan portfolio value. *Risk* **2002**, *15*, 160–162.
43. Höse, S.; Huschens, S. Confidence Intervals for Asset Correlations in the Asymptotic Single Risk Factor Model. In *Operations Research Proceedings 2010*; Hu, B., Morasch, K., Pickl, S., Siegle, M., Eds.; Springer: Berlin/Heidelberg, Germany, 2011. Available online: https://doi.org/10.1007/978-3-642-20009-0_18 (accessed on 15 March 2023). [CrossRef]
44. Ouazad, A.; Kahn, M.E. Mortgage Finance and Climate Change: Securitization Dynamics in the Aftermath of Natural Disasters. *Rev. Financ. Stud.* **2022**, *35*, 3617–3665. [CrossRef]
45. Domeisen, D.I.; White, C.J.; Afargan-Gerstman, H.; Muñoz, Á.G.; Janiga, M.A.; Vitart, F.; Wulf, C.O.; Antoine, S.; Ardilouze, C.; Batté, L.; et al. Advances in the subseasonal prediction of extreme events: Relevant case studies across the globe. *Bull. Am. Meteorol. Soc.* **2022**, *103*, E1473–E1501. Available online: https://journals.ametsoc.org/view/journals/bams/103/6/BAMS-D-20-0221.1.xml?tab_body=pdf (accessed on 15 March 2023). [CrossRef]
46. Meehl, G.A.; Zwiers, F.W.; Evans, J.; Knutson, T.R.; Mearns, L.; Whetton, P. Trends in Extreme Weather and Climate Events: Issues Related to Modeling Extremes in Projections of Future Climate Change. *Bull. Am. Meteorol. Soc.* **2000**, *81*, 427–436. [CrossRef]
47. Lubchenco, J.; Karl, T.R. Predicting and managing extreme weather events. *Phys. Today* **2012**, *65*, 31–37. [CrossRef]
48. Patel, K.B. Managing Climate Risk in Mortgage Markets: A Role for Derivatives. *Chic. Fed Lett.* **2021**, *462*. Available online: https://www.chicagofed.org/publications/chicago-fed-letter/2021/462 (accessed on 15 March 2023). [CrossRef]