Detailed Project Plan (FYP23035)

Title: Developing weather derivatives through analysing weather patterns

Participants:

Wong Hang Nam, Nicole 3035785611

Tsui Tsz Ching, Justin 3035788352

Cheang King Hang, Jeremy 3035785099

Supervisor:
Professor Zou Difan

1. Project Background

1.1 Abstract

Adverse weather can impact economies globally. Weather conditions can dictate the profitability of many weather-dependent industries during different seasons of the year. For instance, aviation, agricultural and transportation industries rely on weather conditions to make business decisions. They depend on accurate weather intelligence technologies in identifying non-catastrophic weather risk in day-to-day business operations. Hence, there has been a rising emphasis on climate-related business risk, which further calls for financial instruments offering protection against poor weather conditions and climate risk. As a result, weather-hedging derivatives has been slowly emerging in the market for businesses to hedge against adverse weather as global warming becomes more pronounced.

1.2 Problem Statement

A rapid increase in natural hazard has been created as a result of a rising number of extreme weather incidents. As reflected in the recent adverse weather incidents of Typhoon 8 and centurial black rain in Hong Kong, the frequency as well as magnitude of impact that adverse weather brought has been surging. According to the Environmental Bureau of Hong Kong, low-lying areas in Hong Kong are predicted to be significantly affected by severe flooding every 5 years (Benz-saliasi, 2021). Climate change has also disproportionately impacted developing countries. The heightened concern for climate risk has escalated market activity in the weather derivatives market trading volume.

1.3 Our project and target deliverables

The deliverables shall include a pricing model of different weather hedging derivatives as a control and a regression model which includes an analysis of important and uncorrelated variables which contribute to the pricing of weather derivatives. In addition, we hope to help businesses gain insights on their weather sensitivity level – the volatility of revenue or cost for a business in a certain industry to a change in weather conditions. In other words, we hope to predict the sensitivity of sales and cost of a business based on climatic elements such as temperature, rainfall and wind etc.

Our project aims to work on derivatives such as swaps, put and call options and straddles. However, the target region of our study is yet to be confirmed. We aim to deliver weather derivatives with weather indexes as the underlying assets. The weather indexes are expected to measure 1. Rainfall Amount 2. Temperature 3. Air Quality respectively.
Our deliverables will include:

1. Develop machine learning models to predict the probability of occurrence of extreme weather events in a given region
2. Apply machine learning analysis in identifying weather patterns for various locations around the world and train the model to conduct predictions on weather forecast
3. Provide weather derivatives' pricing and premium recommendations using multiple pay-off function
4. Predicting the weather sensitivity level for businesses in various sectors
5. Design on contract specifics on various weather derivatives
6. Provide a front-end dashboard on investment advisory for weather derivatives trading for various groups of market participants

2. Basic framework of our project

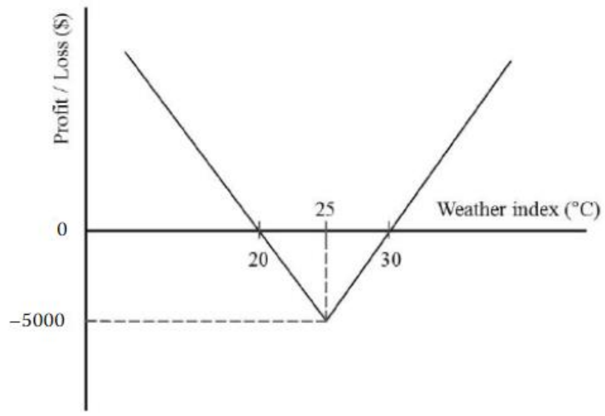
Task	Elaboration

1. Define weather-derivative **contract specifics**	Contract specifics to be defined:
	• Start and maturity date of the contracts
	• Choice of weather index for weather variables such as rainfall and temperature as the underlying assets
	• Pay-off function for each type of derivative contract
	• Premium amount paid to seller from buyer for each type of derivative contract
	• Strike level for each derivative contract
	• Choice of derivatives
	    o Swaps
	    o Put and call options
	    o Straddle

2. Determine the **weather data** for our machine learning model to be trained on	Determine and choose on the methodology on calculating the strike level of the contract • Strike level reflects the expected value of the weather index • Determine the pros and cons of using a 10-year historical average or 20-40 year historical average in calculating the strike level of the weather derivative contract
3. Build a dashboard to	• Select the weather findings to present in the dashboard • Arrange the layout of the dashboard

visualise weather derivatives recommendations for users	

The table below is an example for longing straddle derivative, to be purchased from grapevine producers from an Exchange. We will be using similar frameworks as illustrated below for our final project.

Buyer of the contract	Grapevine producer
Seller of the contract	Financial institutions such as an Exchange which offers derivatives products
Type of derivative contract entered	Long Straddle (Buying of both call and put option of the weather derivative contract)
Type of weather variable to be hedged against	Temperature
Purpose of the buyer of entering into the derivative contract	Concurrently receiving protection from the occurrence of a too high and a too low temperature for wine growing
Strike level of the contract	25 °C
Premium amount	$ 2500
Underlying weather index	Average daily temperature
Protection received by the buyer (grapevine producer)	Call option: offers protection to the grapevine producer (buyer of the derivative) in the case that the temperature rises above 25 °C Put option: offers protection to the grapevine producer in the case that the temperature falls below 25 °C
Payoff function of long straddle in this case	$p(W) = max[0, T \times (S - W)] + max[0, T \times (W - S)] - premium_{put} - premium_{call}$
Graphic representation of the payoff function	 Figure 1. Long straddle
Investment rationale of longing the straddle	Compensation paid to the farmers increases as the deviation from the strike level increases

3. <u>Objectives</u>

3.1 Understand weather pattern

Through this project, we aim to analyse historical weather data from a few select regions where agriculture is the main industry. By assessing many different weather factors such as rainfall, temperature, or air quality, we aim to create models which will help create a clearer understanding on how each of these factors relate to and help predict future weather patterns. We also aim to find the probability in which extreme weather conditions would occur in accordance with an area's climate projections.

3.2 Explore applications of weather derivatives

By understanding weather patterns and how multiple weather factors contribute to climatic conditions of a region, we aim to find the correlation between predicted adverse weather conditions and its financial impact or potential presented risks on the industries within the area, most notably agriculture. Weather derivatives are financial tools that can be helped to mitigate risks presented by these adverse or extreme weather conditions, we aim to find and understand the strategy of usage of weather derivatives, providing an optimal portfolio with pricing and premium recommendations.

3.3 Utilization of machine learning

We aim to utilize machine learning to create predictive models which process historical weather data to forecast future potential financial losses due to predicted adverse weather events, allowing for accurate and optimal use of weather derivatives in risk assessment and prevention. It will also be used to help determine the importance of each of the multitude of weather factors, such that a suitable weighting and pricing can be assigned to each derivative contract, continuously improving the risk prediction and pricing model.

4. <u>Methodology</u>

4.1 **Data Sources selection**

We will choose weather data based on relative abundance and availability to obtain. Weather data from the United States fits this criteria the most, and therefore research will mostly be conducted on areas of interest within the US. Historical weather data is made publicly available by the US government, including factors such as rainfall, temperature, humidity or wind speed. While US agricultural performance is also published by the USDA, detailing historical crop prices and yields on a year by year basis.

4.2 **Data treatment**

To assess the financial impact of extreme weather events, historical data on previous events and their associated costs have to be collected. Sources may include insurance claim, government reports, industry databases and financial records. These data sources then have to integrated and standardised to create a unified dataset, thus involving tasks such as resolving inconsistencies, harmonising data formats.

Feature engineering can also help predicting financial losses through creating relevant indicators that capture relationships between extreme weather events and economic impacts. For example, intensity and duration of the events can be derived and provide insights of factors that contribute to financial losses.

4.3 **Risk Prediction algorithms**

To understand risks of the extreme weather events, we can look into modern climate hedging models. For example, there are Catastrophe Bond Models, Crop Yield Models, Flood Risk Models and Energy Demand models. They demonstrate how we can integrate climate data, statistical analysis and financial principles to manage climate-related risks across various sectors.

4.4 **Derivatives**

In the context of weather hedging, derivatives are contracts whose value are derived from an underlying factors like temperature and humidity. They alloow market participants to hedge against adverse weather conditions and financial impacts. These contracts allow participants to transfer their risks to the market, thereby reducing their exposure to potential losses.

4.5 **Data visualisation**

Since risk prediction models and extreme weather possibilities are complex to understand, we want to present these data in a visually intuitive manner for the stakeholders to make informed decisions. Through charts and graphs, they can have a comprehensive understaning of the potential risks associated with extreme weather events. Factors such as geographical locations, weather types, occurrence and intensity can also provide a clear picture to assess the effects and empowers investors to allocate their resources and implement their risk management strategies.

5. **Risk and potential challenge for the project**

5.1 **Difficulty in obtaining company data**

We foresee the potential difficulty in obtaining confidential and private company data such as sales figure in deducing the volatility of sales caused by changes in weather conditions. Such data may be confidential and not readily available to the public.

To mitigate the risk of unavailability of such data, we may widen our scope and source data from governmental sources or news.

5.2 Difficulty in determining the number of years of training data needed

As mentioned in section 3, the number of years of data needed for training our machine learning model is yet to be determined. The training data for our machine learning model will be weather observations in a given year in history. Using 10 years or 20 years of historical weather observation data for calculating the expected value of weather index can impact the quality of our derivative pricing model significantly. This is because the expected value of weather index will be the strike level for the derivative contract, which will be included in the formula for the payoff function.

To overcome this difficulty, our group will analysis on the pros and cons of using more years of training data on weather observations. It should be noted that there will be a trade-off when a longer timeframe on training data is used. Although using more years of training data can yield a higher accuracy and a fuller picture, a shorter timeframe on weather observations data will give a better demonstration of the more recent climatic conditions of a region.

6. **Proposed Schedule**

Date	
1 Oct 2023	Detailed project plan Project webpage
Phase 1: Rainfall derivative	
15 Oct 2023	Complete data collection and cleaning
11 Nov 2023	Complete prediction model training
15 Dec 2023	Create first rainfall derivative contract
25 Dec 2023	Create dashboard
8-12 Jan 2024	First presentation
21 Jan 2024	Preliminary implementation Detailed interim report
Phase 2: Temperature/Air quality derivatives	
11 Feb 2024	Complete data collection
3 Mar 2024	Complete Temperature/Air quality prediction model training
24 Mar 2024	Create Temperature/Air quality derivative contract
Phase 3: Final Project	
31 Mar 2024	Complete derivative portfolio design
7 Apr 2024	Complete project webpage
15-19 Apr 2024	Final presentation
23 Apr 2024	Finalized tested implementation Final Report

References

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