Climate Risk Hedging

Thomas Lorans

May 17, 2024

Contents

1 Introduction **1**

2 Random Variables **3**

3 Regression **7**
  3.1 β estimation 7

4 Mimicking the Market Portfolio **9**

5 Time Series **11**

6 Tracking Portfolio for News **13**

7 Climate Hedge Targets **15**
  7.1 Climate News Series 15
  7.2 Climate News Innovation 15
    7.2.1 Climate News Shock 16
  7.3 Portfolio Exposure to Climate News Innovations 16
    7.3.1 Multifactor Regression 16
    7.3.2 Climate News Innovations as a Risk Factor 16

8 Climate Risk Mimicking Portfolio **17**

Chapter 1

Introduction

We consider alternative approaches for climate risk hedging. All approaches share the same goal: to be long stocks that do well in periods with unexpectedly bad news about climate risks, and short stocks that do badly in those scenarios.

Chapter 2

Random Variables

We model stock returns as *random variables.* A random variable can take one of many values, with an associated probability. For example, the gross return on a stock can be one of four values as shown in Table 2.1.

R	$P(R)$
1.1	0.6
1.2	0.1
0.7	0.25
0.0	0.05

Table 2.1: Example of a gross return distribution.

Each value is a possible *realization* of the random variable. You can experiment with this in Python using the following code:

```python
import numpy as np

# Define the possible returns and their probabilities
returns = np.array([1.1, 1.2, 0.7, 0.0])
probabilities = np.array([0.6, 0.1, 0.25, 0.05])

# Generate a random return
print(np.random.choice(returns, size=1, p=probabilities))
```

Of course, stock returns can take on many more values than just four, but this is a simple example.

The *distribution* of the random variable is a listing of the values it can take, along with their associated probabilities. For example, the distribution of the random variable in Table 2.1 is:

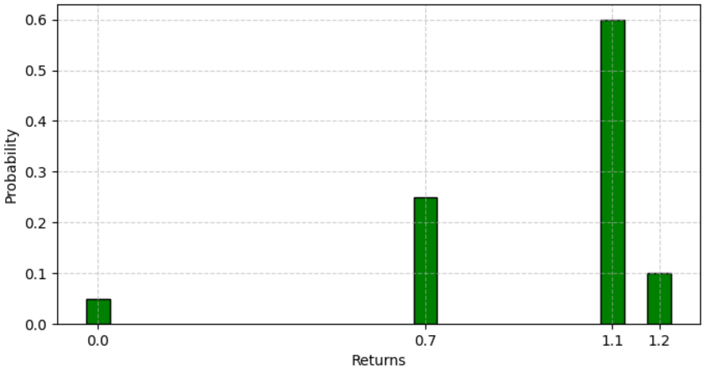

Figure 2.1: Example of a random variable distribution.

Another way to think of a random variable is as a *function* that maps "states of the world" to real numbers. For example, the random variable in Table 2.1 could be:

R	States of the world	$P(R)$
1.1	New product works, competitor burns down	0.6
1.2	New product works, competitor ok.	0.1
0.7	Only old products work	0.25
0.0	Factory burns down, no insurance.	0.05

Table 2.2: Random variable as a function mapping states of the world to real numbers.

The probability really describes the external events that define the states of the world. Usually, we can't name those events, so we just use the probabilities that the stock return takes on various values.

Chapter 3

Regression

We will run regression, for example of a return on the market return:

$$R_t = \alpha + \beta R_{m,t} + \epsilon_t \tag{3.1}$$

where R_t is the return on the asset, $R_{m,t}$ is the return on the market portfolio, α is the intercept, β is the slope coefficient and ϵ_t is the regression residual.

We may sometimes run multiple regressions of returns on the return of several portfolios, for example:

$$R_t = \alpha + \beta R_{m,t} + \gamma R_{p,t} + \epsilon_t \tag{3.2}$$

where R_p is the return on the portfolio of interest.

The generic form is:

$$y_t = \alpha + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \ldots + \beta_n x_{n,t} + \epsilon_t \tag{3.3}$$

3.1 β estimation

Starting with:

$$y_t = \alpha + \beta x_t + \epsilon_t \tag{3.4}$$

With the usual assumption that errors are uncorrelated, we have the right hand variables $E(\epsilon_t x_t) = 0$ and $E(\epsilon_t) = 0$.

Multiplying both sides by $x_t - E(x_t)$ and taking expectations:

$$\beta = \frac{Cov(y,x)}{Var(x)} \tag{3.5}$$

Chapter 4

Mimicking the Market Portfolio

Chapter 5

Time Series

Chapter 6

Tracking Portfolio for News

Chapter 7

Climate Hedge Targets

One challenge with designing portfolios that hedge climate risks is that there is no unique way of choosing the hedge target. Climate change is a complex phenomenon and presents a variety of risks, including physical risks such as rising sea levels and transition risks such as the dangers to certain business models from regulations to curb emissions. Different risks may be relevant for different investors, and these risks are imperfectly correlated. In addition, climate change is a long-run threat, and we would thus ideally build portfolios that hedge the long-run realizations of climate risk, something difficult to produce in practice. To overcome these challenges, Engle *et al.* (2020) [**?**] argue that the objective of hedging long-run realizations of a given climate risk can be achieved by constructing a sequence of short-lived hedges against *news* (one-period innovation in expectations) about future realizations of the risk. Following the initial work of Engle *et al.* (2020), researchers have developped a variety of climate news series, capturing a variety of climate risks.

7.1 Climate News Series

Describe some climate new series.

7.2 Climate News Innovation

Building on the work of Engle *et al.* (2020), we use the $AR(1)$ innovations of each climate news series as the hedge targets. For a given climate news series

c, we denote these $AR(1)$ innovation in month t as $CC_{c,t}$.

7.2.1 Climate News Shock

7.3 Portfolio Exposure to Climate News Innovations

7.3.1 Multifactor Regression

7.3.2 Climate News Innovations as a Risk Factor

Chapter 8

Climate Risk Mimicking Portfolio

The mimicking portfolio approach combines a pre-determined set of assets into a portfolio that is maximally correlated with a given climate change shock, using historical data. To obtain the mimicking portfolios, we estimate the following regression model:

$$CC_t = wR_t + \epsilon_t \tag{8.1}$$

where CC_t denotes the (mean zero) climate hedge target in month t, w is a vector of N portfolio weights, R_t is the $N \times 1$ vector of demeaned excess returns and ϵ_t is the regression residual. The portfolio weights are estimated each month using a rolling window of T months of historical data.