

# Climate Risk Hedging

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# 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

## Simple Economic Tracking Portfolio

The portfolio constructed here has unexpected returns with maximum correlation with news about future macroeconomic variables.

Empirical finance has a long tradition of explaining current returns with other current returns.

### 2.1 Basics

#### 2.1.1 Modelling Returns

#### 2.1.2 Statistics

### 2.2 Forming Tracking Portfolio with Regression

#### 2.2.1 Regression

#### 2.2.2 Tracking Portfolio

A tracking portfolio for any variable  $y$  can be obtained as the fitted value of a regression of  $y$  on a set of base asset returns. The portfolio weights for the economic tracking portfolio for  $y$  are identical to the coefficients of an OLS regression. If  $y$  happens to be a state variable for asset pricing, then a multi-factor model holds with one of the factors being the  $y$ 's tracking portfolio.

However, even if  $y$  is not a state variable for asset pricing, its tracking portfolio is still an interesting object, since it reveals changes in market expectation about  $y$ .

The following three statements are equivalent description of an economic tracking portfolio:

1. the portfolio has the minimum variance out of all portfolios with a given beta (univariate regression coefficient) in a regression portfolio return on  $y$ .
2. has returns with the maximum possible correlation with  $y$ .
3. has the highest  $R$ -squared in a regression of  $y$  on the portfolio returns.

These properties come directly from the definition of an OLS regression.

## **2.3 Python Project: Tracking the Market Portfolio**

## **2.4 Conclusion**



# Chapter 3

## Economic Tracking Portfolio for News

### 3.1 Basics

#### 3.1.1 Time Series

### 3.2 Tracking the Unexpected

it constructs tracking portfolios for future (not current) economic variables, since asset returns reflect information about future cash flows and discount rates. Second, as a consequence, it uses only the unexpected component of returns (not total returns) in constructing the tracking portfolios.

#### 3.2.1 Returns Predictability

Suppose expected returns  $x_t = E_t(R_{t+1})$  follow an AR(1) process:

$$x_t = \phi x_{t-1} + \epsilon_t^x \quad (3.1)$$

$$R_{t+1} = x_t + \epsilon_{t+1}^R \quad (3.2)$$

#### 3.2.2 Return Identity

If an asset lasts one period, returns are, by definition:

$$R_{t+1} = \frac{D_{t+1}}{P_t} \quad (3.3)$$

where  $D_{t+1}$  is the dividend paid at  $t + 1$  and  $P_t$  is the price at  $t$ . We don't have  $P_{t+1}$  in this one period case because the asset lasts only one period.

We can take expectation:

$$E_t(R_{t+1}) = \frac{E_t(D_{t+1})}{P_t} \quad (3.4)$$

and solve for price or price-dividend ratio:

$$P_t = \frac{E_t(D_{t+1})}{E_t(R_{t+1})} \quad (3.5)$$

$$\frac{P_t}{D_t} = \frac{E_t(D_{t+1}/D_t)}{E_t(R_{t+1})} \quad (3.6)$$

These formula represent the price as the discounted value of future dividends. If expected future dividends are higher, the price goes up. If expected returns rise, the price goes down. Why? Perceived risk goes up, so investors try to sell the asset, which lowers the price. So, the price or the price-dividend ratio should move only if expected returns or expected dividends move. That is, if the discount rate or expected future cash flows change.

From here, we can reformulate this in terms of returns. We can take surprises  $\Delta E_{t+1}$  for the price:

$$\Delta E_{t+1}(P_t) = \frac{\Delta E_{t+1}(D_{t+1})}{\Delta E_{t+1}(R_{t+1})} \quad (3.7)$$

with  $\Delta E_{t+1}(P_t) = 0$  because the price is known at  $t$ .

### Time-Varying Expected Returns

To see if returns are predictable, we run a regression:

$$R_{t+1} = a + bx_t + \epsilon_{t+1} \quad (3.8)$$

This is the regression of tomorrow's return on today's information  $x_t$ . If we find a big  $b$  or large  $R^2$ , we can say that returns are (somewhat) predictable. If not, we can say that returns are not predictable. The regression answer the question: can we predict returns using today's information?

Equivalently, the forecasting regression implies:

$$E_t(R_{t+1}) = a + bx_t \quad (3.9)$$

This is the expectation of tomorrow's return given today's information. The expected return can vary over time, being higher or lower depending on the signal  $x_t$ . Therefore, the forecasting regression measures whether expected returns vary over time.

*Predictable* doesn't mean perfectly. Expected means conditional mean, but there is a lot of variance. Risk includes unexpected positive returns.

Use forecasting regression in finance to understand how the right hand variable is formed, from expectations of the left hand variable.

If we want to check a forecaster, we run:

$$\text{temperature}_{t+1} = a + b \times \text{forecast made at } t + \epsilon_{t+1} \quad (3.10)$$

In terms of *causality*, we think the forecaster gets information about future temperature, this causes him to issue a forecast. If it's a good forecast, then  $b = 1$  with a good  $R^2$ . What we learn is not what causes the weather to be good or bad but how the forecast is formed.

### 3.2.3 Tracking Portfolios

This paper constructs portfolios with unexpected returns that are maximally correlated with unexpected components of future  $y$ . Specifically, the target variable is *news* about  $y_{t+k}$ , where  $y_{t+k}$  is a macroeconomic variable in period  $t + k$ .

News is innovation in expectations about  $y_{t+k}$ , with notations:

$$\Delta E_t(y_{t+k}) = E_t(y_{t+k}) - E_{t-1}(y_{t+k}) \quad (3.11)$$

For example,  $\Delta E_t(y_{t+k})$  can be the news the market learns in July 2021 about the GDP growth rate in 2022.

The tracking portfolio returns are:

$$r_{t-1,t} = bR_{t-1,t} \quad (3.12)$$

where  $r_{t-1,t}$  is the return of the tracking portfolio,  $R_{t-1,t}$  is a column vector of asset returns from the end of period  $t - 1$  to the end of period  $t$ , and  $b$  is a row vector of portfolio weights.

The tracking portfolio is constructed using unexpected returns on the base assets. The unexpected returns are actual returns minus expected returns:

$$\tilde{R}_{t-1,t} = R_{t-1,t} - E_{t-1}(R_{t-1,t}) \quad (3.13)$$

The portfolio weights are chosen so that  $\tilde{r}_{t-1,t}$  is maximally correlated with  $\Delta E_t(y_{t+k})$ .

Estimating tracking portfolios for news is only slightly more complicated than estimating simple tracking portfolios. One can always write a projection equation of news on unexpected returns. The key assumption in this paper is that innovations in returns reflect innovations in expectations about future variables, so that the vector  $a$  has non-zero elements in the projection equation:

$$\Delta E_t(y_{t+k}) = a\tilde{R}_{t-1,t} + \eta_t \quad (3.14)$$

where  $\eta_t$  is the component of news that is orthogonal to the unexpected returns. Since unexpected returns reflect news about future cash flows and discount rates,  $a$  will generally be non-zero for any variable correlated with future cash flows or discount rates (there is no intercept in the equation above).

It seems at first glance that one needs to obtain  $\Delta E_t(y_{t+k})$ , the period  $t$  news about  $y_{t+k}$ , to run the regression. In fact, all that is needed is  $\tilde{R}_{t-1,t}$ , the unexpected returns. The realization of  $y_{t+k}$  can be written as the sum of the expectation in period  $t-1$ , the innovation in expectations in period  $t$ , and the innovation in expectations from period  $t$  to period  $t+k$ :

$$y_{t+k} = E_t(y_{t+k}) + e_{t,t+k} = E_{t-1}(y_{t+k}) + \Delta E_t(y_{t+k}) + e_{t,t+k} \quad (3.15)$$

The second assumption made here is that expected returns on the base assets in period  $t$  are linear functions of  $Z_{t-1}$ , a vector of control variables known at period  $t-1$ :

$$E_t(R_{t-1,t}) = dZ_{t-1} \quad (3.16)$$

While this assumption is a potential source of model misspecification, one might expect the empirical results to be relatively robust to this form of misspecification, since asset returns are largely unpredictable at short horizons.

Last, for notational convenience, define the projection equation of lagged expectations of  $y$  on the lagged control variables:

$$E_{t-1}(y_{t+k}) = fZ_{t-1} + \mu_{t-1} \quad (3.17)$$

Combining the last three equations, we obtain:

$$y_{t+k} = bR_{t-1,t} + cZ_{t-1} + \epsilon_{t,t+k} \quad (3.18)$$

where  $b = a$ ,  $c = f - ad$ , and  $\epsilon_{t,t+k} = e_{t,t+k} + \eta_t + \mu_{t-1}$ . This is a regression equation with realized future  $y$  on the left-hand side and period  $t$  returns and period  $t - 1$  control variables in the right-hand side. It is consistent because the three components of  $\epsilon_{t,t+k}$  are orthogonal to both  $R_{t-1,t}$  and  $Z_{t-1}$ .

This regression produces  $bR_{t-1,t}$ , the portfolio returns having unexpected components maximally correlated with  $\Delta E_t(y_{t+k})$ . The portfolio weights are  $b$ . This equation is atheoretical and depends only on the assumption that changes in expectations about future  $y$  are reflected in asset returns, and that expected asset returns are a function of the lagged control variables.

### 3.3 Python Project: Tracking Inflation

### 3.4 Conclusion



# Chapter 4

## Climate Risk Mimicking Portfolio

How investors can mitigate the risks that climate change poses to their portfolios is a pressing question. This is particularly important since many of the effects of climate change are sufficiently far in the future that neither derivatives or specialized insurance markets are available to directly hedge them. Instead, investors are largely forced to insure against realizations of climate risk by building hedge portfolios on their own.

Engle *et al.* (2020) propose an approach to hedging climate risk, using climate news and the mimicking portfolio approach, following the methodology we have seen in the previous chapter. The key question is how to measure news in the case of climate change?

### 4.1 Hedging Climate News

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:

$$CC_t = wR_t + \epsilon_t \tag{4.1}$$

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 unexpected excess returns and  $\epsilon_t$  is the regression residual. The portfolio weights are estimated each month using a rolling window of  $T$  months of historical data.

The approach is intuitive: the portfolio overweights assets that have rise in value in the arriveal of climate change news, and underweights assets that fall in value in the same situation. In doing so, the hedge portfolio profits when adverse climate change news occurs.

## 4.2 Python Project: Transition Risk Hedging

## 4.3 Conclusion