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The integration of climate models and data in the context of strategic asset allocation

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Abstract

Climate change stands as one of the most pressing social challenges of the 21st century. Broadly defined in finance as the potential loss of asset value resulting from climate change, climate risk encompasses both physical and transitional risks. Given its pivotal role in financing industry and fostering a green economy, the financial sector is increasingly focused on managing these risks. Leveraging datasets such as the NGFS, MSCI, and Schiller databases, our paper proposes steps for integrating climate risk into portfolio management, utilizing a methodology based on climate scenarios. Specifically, we analyze the behavior of GDP and CPI across four major economies (US, UK, China, France) under various NGFS climate scenarios. Then, we assess the sensitivity of prospective returns to climate scenarios and employ two strategies (Sharpe ratio and Black-Litterman model) to integrate NGFS scenarios into portfolio allocation. For all scenarios, returns of equity decrease across each country, with a notable decline in the "Too Little Too Late" scenario. Moreover, portfolio allocation results in an not diversified, and thus risky, portfolio. While these findings should be approached with caution, they illustrate that it is becoming imperative for asset managers to incorporate climate risk into their analyses.

Keys words: climate risk, NGFS scenario, portfolio management.

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Acronyms

CAPE	:	Cyclically Adjusted Price Earnings
CAPM	:	Capital Asset Pricing Model
CO_2	:	Carbon dioxide
CPI	:	Consumer Price Index
GCAM	:	One of the IAMs model's name
GDP	:	Gross Domestic Product
IAMs	:	Integrated Assessment Models
MESSAGEix-GLOBIOM	:	One of the IAMs model's name
MSCI	:	Morgan Stanley Capital Investment
MSE	:	Mean Squared Error
NDCs	:	Nationally Determined Contributions
NGFS	:	Network for Greening the Financial System
NIESR	:	National Institute of Economic and Social Research
NiGEM	:	National Institute Global Econometric Model
REMIND-MAgPIE	:	One of the IAMs model'name
UK	:	United Kingdom
US	:	United States

Introduction

The climate crisis is emerging as a central axis of political debates and strategy actions in the 21st century, thus revealing its fundamental importance. The recognition of potential impacts and risks of climate change in the global economy and the financial sector is undeniable (Allen et al. 2019). The risks are often classified into two main categories: physical risks and transition risks. Physical risks are related to the direct impacts of climate change on the economy, such as extreme weather events, sea-level rise, and changes in temperature and precipitation patterns. Transition risks are related to the effort to mitigate climate change and adapt to its impacts, such as changes in policy, technology, and market preferences. The financial sector is particularly exposed to these risks, as it is directly affected by the physical impacts of climate change and by the economic and financial impacts of the transition to a low-carbon economy. Klomp 2014 has shown in research involving 140 countries that natural disasters raise the likelihood of commercial banks defaulting. Clerc 2021 believes that the failure of actors and financial markets to account for climate risk, leading to suboptimal pricing of this risk and the misallocation of financing towards activities that are the highest emitters of greenhouse gases, could render climate risk systemic in nature. This is because it has the potential to impact all countries worldwide and economic stakeholders.

Hence, to maintain adequate resilience to the negative impacts of climate risks, financial system actors have a significant role to play in the economy by driving this change through financing the green industry and economy. To achieve this, they must be able to systematically identify, measures and manage climate change risks (Figaro 2023). Moreover, to mitigate its adverse effects, the international community has committed to countering the detrimental impacts of this climate evolution. It was then, thanks to the 2015 Paris agreement, that countries around the world agreed, among other objectives, to work towards transitioning to a low-carbon economy in the long term.

Financial institutions have to develop methodologies applicable to their balance sheets and portfolios in order to manage transition risk. However the specificities of climate risk –its forward-looking nature and distinctive impacts over various time horizons, sectors and geographies, as well as the lack of relevant data– make their modeling complex and challenging.

To comply with regulators' requirements in the transition to a low-carbon economy, many asset owners and asset managers aims to explore various methodologies for integrating climate risk into their asset allocations. Our main goal will be to examine how financial data respond to macroeconomic shocks stemming from the various climate scenarios provided by the NGFS. To achieve that, we need relevant data and a suitable model to anticipate and manage future risks related to climate change. In order to accomplish this, we require pertinent data and an appropriate model to predict and address future risks associated with climate change.

The organization of the paper is as follows. First we address the literature review on the impact of climate change on the financial sector, then we detail the data we intend to use. After that, in the third section, we estimate forward returns and analyse their sensitivities to macroeconomic variables. In section 4, we examine climate change's effects on stock markets. And finally, in section 5 we illustrate how climate change influences portfolio allocation strategies.

1 Literature Review

In this section, we'll explore various methodologies related to climate risk in the financial sector as well as the challenges that arise from them. The literature on portfolio construction is vast, we do not attempt to survey it here in detail. Instead, we highlight only few mayor developments that are relevant to our work.

1.1 Methodology related to climate risk

Much of the research on the climate crisis relies on scenario analysis, a method that utilizes a set of assumptions to predict future outcomes. The specific scenarios employed can vary depending on the approach taken. There are two primary approaches to scenario analysis: the top-down and bottom-up approaches. The top-down approach is a macroeconomic and long term analysis. It consists of studying the effects of the increase in climate risks on macroeconomic variables. In contrast, the bottom-up approach involves microeconomic analyses and relies on detailed data specific to individual companies or sectors on the assets side. In the literature, these scenarios are derived from models such as the "Integrated Assessment Models" (IAMs), the "National Institute Global Econometric Model" (NIGEM), and Climate MAPS. The input variables in these models incorporate forecasts of climate shocks (price of CO_2, changes in energy consumption, the variation in greenhouse gas emissions, and forecasts of the economic impact of physical risk)

1.1.1 Integrated Assessment Models (IAMs)

Integrated Assessment Models (IAMs) merge detailed models of energy system technologies with simplified economic and climate science models to evaluate various population, economic, and technological pathways. This integration allows for an assessment of the feasibility of achieving specific climate change mitigation goals (Rogelj et al. 2018). It is widely used in the literature, for example, by Battiston et al. 2017 and Monasterolo, Zheng, and Battiston 2018 to develop a climate stress-test methodology for assessing the credit risk of fossil fuel and renewable energy project portfolios of two Chinese development banks. Furthermore, future trajectories in terms of energy transition have been constructed by experts from the NGFS, a network of central banks and financial regulators for the financial system, utilizing IAMs models.

To construct sufficiently robust scenarios with sectoral and geographical granularity levels, the NIGEM is well-suited for modeling the impacts of climate change on macroeconomic variables.

1.1.2 National institute Global Econometric Model (NiGEM)

It is a transparent, peer reviewed global econometric model developed by the "National Instute of Economic and Social Research"(NIESR) over 30 years of regular use. It represents a closed world, where outflows from one country or region are matched by inflows into other countries and regions. Key behavioural equations are econometrically estimated using historical data. This ensures that the dynamics and key elasticities of the model fit the main characteristics of individual country data. The model is used by policymakers and private sector organisations around the world for economic forecasting, scenario analysis and stress testing (NIESR 2020). To evaluate the impact of climate change on a wide range of macroeconomic variables through specific transmission channels, the NGFS uses the NiGEM as an enhancement to the basic IAM (Integrated Assessment Model) framework. The NiGEM model allows for the construction of robust scenarios with sectoral and geographical granularity, enabling a clearer assessment of the effects of climate change. Recently, Bongiorno et al. 2022 utilized another model, Climate MAPS, to assist actuaries and financial institutions in comprehending the potential long-term implications of climate change on financial markets.

1.1.3 Climate MAPS

Climate MAPS is a top-down modeling tool developed through a collaboration between Ortec Finance and Cambridge Econometrics. This innovative tool melds climate science with macro-economic and financial modeling to weave quantified systemic climate risks and opportunities —encompassing both physical and transition aspects— into traditional multi-horizon, real-world scenario sets.

Bongiorno et al. 2022 leveraged Climate MAPS to examine the effects of three distinct climate scenarios on GDP, ultimately deducing that each scenario would precipitate a decline in GDP as a mean to illustrate the potential impacts of climate change on financial markets. The study further explored the repercussions of GDP shifts on stock prices by employing a stochastic model. The findings elucidated that, across all scenarios, global equity returns lag behind those projected in the baseline scenario, underscoring the economic vulnerabilities and the potential for reduced investment returns in the face of climate change.

We have just explored several approaches commonly employed to model climate risk within the financial sector. However, it is crucial to acknowledge the various challenges encountered in this endeavor.

1.2 Limitations

In order to measure climate risk, there are some important challenges we must be aware of.

Firstly, there's a notable lack of forward-looking data, complicating the incorporation of the non-linear aspects of climate-related risks (NGUEMDJO 2023). Moreover, back-testing climate models is challenging due to the often shorter historical data series compared to conventional financial metrics; this casts doubt on the reliability of climate models (*Les banques et le climat* 2024).

Secondly, the analysis of climate change scenario modeling is complex and nuanced. These scenarios are based on a set of assumptions that may underestimate the risks (Trust et al. 2024).

Finally, given the uncertain future, random variations in future economic variables and investment returns over the short term may lead to outcomes that significantly diverge from the expected long-term average experience. This is true for all stochastic financial models but is particularly important here because there is material uncertainty in all aspects of climate scenario modelling (Bongiorno et al. 2022).

1.3 Portfolio Construction

Most research on portfolio optimization is built on the original idea proposed by Markowitz. Markowitz outlined a two-step process for selecting a portfolio. Initially, an investor develops expectations about the future returns of assets, which are represented as a vector μ, and their covariances, shown in a covariance matrix Σ. This matrix highlights the volatilities of asset returns and the correlations between them. These expectations are crucial for the next step, which involves optimizing the portfolio using these quantities.

He introduced the expected returns–variance of returns (E–V) rule. This principle suggests that an investor aims to maximize the expected return of a portfolio while maintaining its variance, or risk, below a certain level (Boyd et al. 2024).

Over the years, various authors have built upon Markowitz's ideas. For example, Sharpe 1994 introduced the Sharpe Ratio to evaluate an investment's performance by considering the risk involved. Similarly, Black and Litterman 1990 developed an optimization model that takes investor expectations into account to create a relevant allocation reflecting their forecasts. Despite the main critique of these models, which assumes a normal distribution of returns, they remain widely used in practice.

2 Data review

In this study we are using two publicly accessible databases.The first database we will use is the NGFS database[1] to source macro-economic data for the various climate scenarios. The second database is the Schiller database[2] to estimate how US equity expected returns are sensitive to shocks in GDP and Inflation. We also use Bloomberg data from the MSCI (Morgan Stanley Capital Investment) index. These data will enable us to construct our portfolio at the end of our study.

These are the main databases that we will use, but we will use other data that we will introduce at the appropriate time.

2.1 NGFS database

NGFS stands for Network For Greening the Financial System. It was launched at the Paris "One Planet Summit" by eight central banks and supervisors. Since then, the membership of the Network has grown dramatically, across the five continents. This network aims to help strengthen the global response required to meet the goals of the Paris agreement and to enhance the role of the financial system to manage risks.

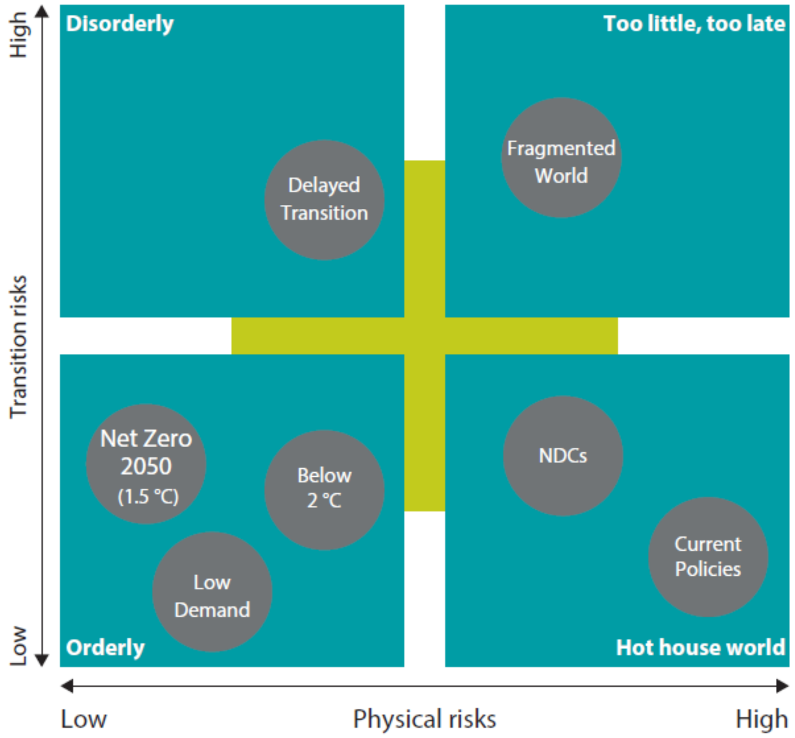
2.1.1 NGFS scenarios overview

The NGFS has developed long-term climate scenarios to inform analysis and guide policy around the world. The NGFS climate scenarios map out how economies might evolve under different assumptions. The underlying assumptions characterize each scenario. There are 7 of them, divided into 4 groups:

- Orderly scenarios: Low Demand, Below 2°C and Net Zero 2050

[1] accessible from the link https://www.ngfs.net/ngfs-scenarios-portal/data-resources/
[2] accessible via the link https://shillerdata.com/

- Disorderly scenario: Delayed Transition
- Hot house world scenarios: Current policies and Nationally Determined Contributions (NDCs)
- Too-little-too-late scenario: Fragmented World



Source: NGFS scenario for central banks and supervisors

Figure 1: NGFS Scenarios

Each NGFS scenario explores a different set of assumptions about the evolution of climate policy, emissions, temperatures and the impacts of physical risks.

- Delayed Transition assumes annual emissions do not decrease until 2030. Strong policies are needed to limit warming to below 2°C. Negative emissions are limited.
- Net Zero 2050 limits global warming to 1.5 °C through stringent climate policies and innovation, reaching global net zero CO_2 emissions around 2050.
- Below 2 °C gradually increases the stringency of climate policies, giving a 67% chance of limiting global warming to below 2 °C.

- Low Demand assumes that significant behavioural changes – reducing energy demand – in addition to (shadow) carbon price and technology induced efforts, would mitigate pressure on the economic system to reach global net zero CO_2 emissions around 2050.
- Fragmented World assumes a delayed and divergent climate policy response among countries globally, leading to high physical and transition risks. Countries with net zero targets achieve them only partially (80% of the target), while the other countries follow current policies.
- Nationally Determined Contributions (NDCs) includes all pledged targets even if not yet backed up by implemented effective policies.
- Current Policies assumes that only currently implemented policies are preserved, leading to high physical risks.

The assumptions in the different scenarios can be summarized in table 1. This table maps out key features of the scenario narrative and their macro-financial risk implications stemming from transition or physical risk. Green means “low risk”, yellow means “medium risk”, red means “high risk”. For instance, within the "End of Century (Peak) Warming - Model Average" column, scenarios such as Low Demand (New) and Net Zero 2050 are marked in green, indicating "low risk". Meanwhile, scenarios like Below 2°C and Delayed Transition are highlighted in yellow, signifying "medium risk," and all other scenarios are in red, denoting "high risk."

Quadrant	Scenario	End of century (peak) warming - model average	Policy reaction	Technology change	Carbon dioxide removal	Regional policy variation
Orderly	Low Demand (NEW)	1.4°C (1.6°C)	Immediate	Fast change	Medium use	Medium variation
	Net Zero 2050	1.4°C (1.6°C)	Immediate	Fast change	Medium-high use	Medium variation
	Below 2°C	1.7°C (1.8°C)	Immediate and smooth	Moderate change	Medium use	Low variation
Disorderly	Delayed Transition	1.7°C (1.8°C)	Delayed	Slow/Fast change	Medium use	High variation
Hot house world	Nationally Determined Contributions (NDCs)	2.4°C (2.4°C)	NDCs	Slow change	Low use	Medium variation
	Current Policies	2.9°C (2.9°C)	None - current policies	Slow change	Low use	Low variation
Too-little-too-late	Fragmented World (NEW)	2.3°C (2.3°C)	Delayed and Fragmented	Slow/ Fragmented change	Low-medium use	High variation

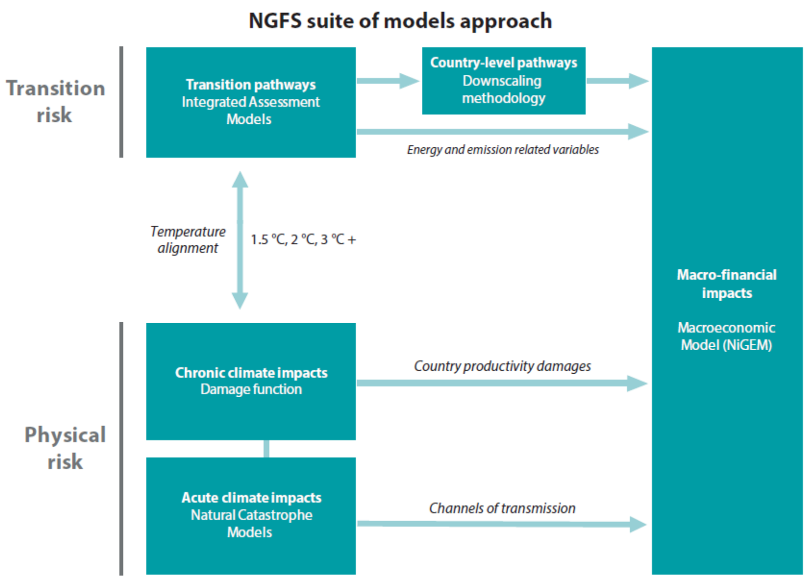
Table 1: NGFS scenarios assumptions by key assumptions

2.1.2 The NGFS macroeconomic model and data

The NGFS scenarios are based on different models. Each model makes it possible to estimate and capture different climatic or macroeconomic aspects separately but in a robust manner. The NGFS models are grouped into:

- **Physical risk models** : Those include acute and chronic physical risk models. Acute physical risk models models impacts from extreme weather events at a country level. Four hazards are considered : cyclone, drought, flood and heatwave. In the meantime, the chronic physical risk is modelled by an aggregated damage function.

- **Transition risk models**: Include three Integrated Assessment Models (IAMs), specifically REMIND-MAgPIE, GCAM and MESSAGEix-GLOBIOM. These models measure the impact of the assumptions made in the scenarios on energy, emissions and sectors relating to transition risk in general.
- **Country-level downscaling** is applied to IAMs world regions to allow us to get information at a national or regional level with 184 countries and more than 30 regions.
- **The macroeconomic model**: This is the NiGEM model. It uses both transition and physical risk models in order to understand how these risks influence key macroeconomic variables. It is this model that will interest us in our study



Source: NGFS scenario for central banks and supervisors

Figure 2: NGFS suite of models approach

As illustrated in figure 2, the NiGEM model database contains all the integrated assessment models and their outputs in order to measure the impact on macroeconomic variables. We perform a series of treatments on the raw data recovered.

2.1.3 Database processing

This section explains our methodology to aggregate data by models, scenario and regions or country.

To capture the inherent uncertainty in modeling climate-related macroeconomic and financial risks, the NGFS scenarios utilize various models and explore a broad range of scenarios across different regions and sectors. The NGFS suite-of-models is harmoniously integrated, generating a comprehensive array of data on transition risks, physical risks, and economic impacts.

The macroeconomic model consists of the NiGEM model to understand the consequences of transition and physical risks on key macro-financial fundamentals. The transition pathways for the NGFS scenarios have been developed using Integrated Assessment Models (REMIND-MAgPIE, GCAM, and MESSAGEix-GLOBIOM) and coupled with a macroeconomic model (NiGEM) to provide an extended range of macroeconomic insights.

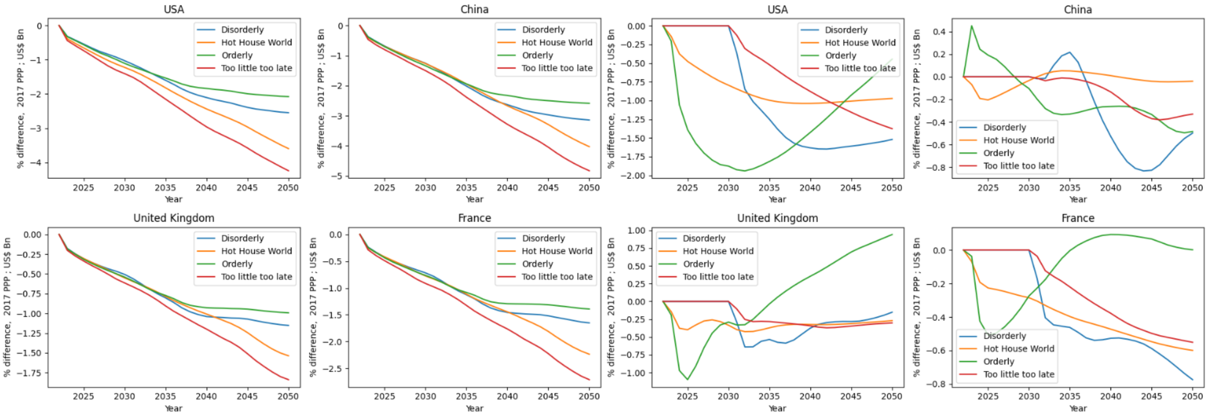
One potential approach was to analyze various models for comparison purposes. However, due to time limitations, we opted to aggregate them into a single model by calculating the average of each variable across all models.

For the scenarios, we applied a similar aggregation process across the different groups: Orderly scenarios, Disorderly scenarios, Hot House World scenarios, and Too-little-too-late scenarios. This brings us to 4 scenarios instead of 7.

Finally, we chose to focus on four countries –The United States, United Kingdom, China, and France– due to their extensive available market data and the substantial research previously conducted on the impact of climate risk in their respective financial sectors. These countries provide an ideal foundation for our analysis, allowing us to draw meaningful insights into the potential consequences of climate risks on their economies and financial systems.

2.1.4 Descriptive analysis of data

In our data, we focus on the evolution of macroeconomic variables according to the different scenarios that we have grouped together, as explained above. Therefore, according to the NGFS scenarios, the evolution of GDP will be as follows over the coming years:



Chronic physical risks

Transition risk

Figure 3: Evolution of GDP

We can see that the variations in GDP due to chronic physical risks have the same appearance for all the countries considered. Moreover, whatever the country, the graphs representing chronic physical risks show an increasingly steep decline in GDP depending on the scenario, in the following order: orderly, disorderly, hot house world, too little too late. This order was expected given the definition of the scenarios. We can also see that GDP declines are less significant in United Kingdom and France than in the United States and China. This could be explained by stricter climate measures in Europe.

The change in GDP due to transition risk, on the other hand, seems less orderly. In the United States, United Kingdom and France, the orderly scenario has the least negative impact in the long term, but has the most negative impact in the early years. The other scenarios have slightly different impacts depending on the country. The case of China is different from that of the other 3 countries. The order of severity of the scenarios seems to be reversed Compared to the other countries. In particular, the orderly scenario has a positive impact in the first few years, but this impact deteriorates sharply over time. The USA and China are the world's most industrialized countries. They are therefore more affected by transition risk. They will also experience greater pressure on the prices of their export products, as countries strive to achieve a low-carbon economy.

Then, we can analyse GDP trends when all the risks are combined.

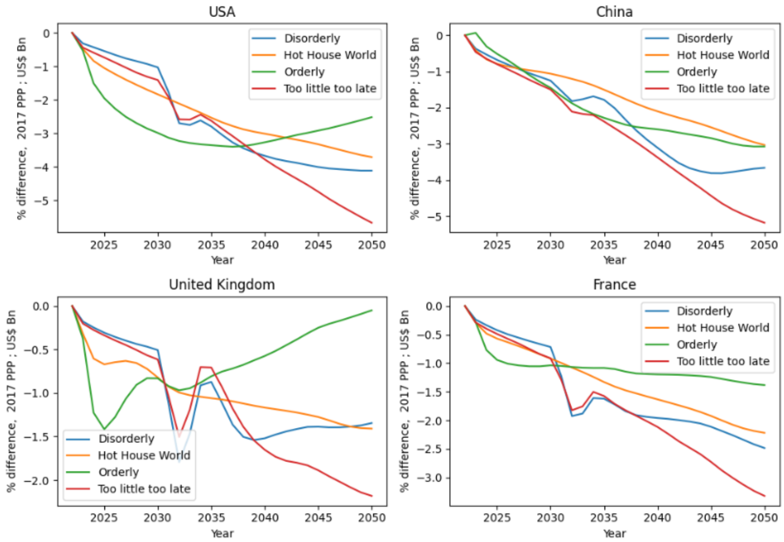
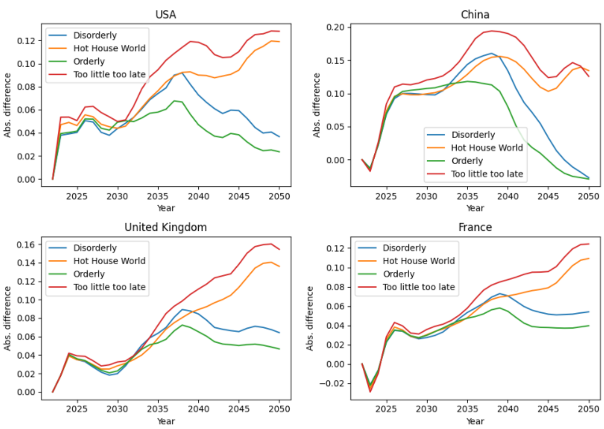
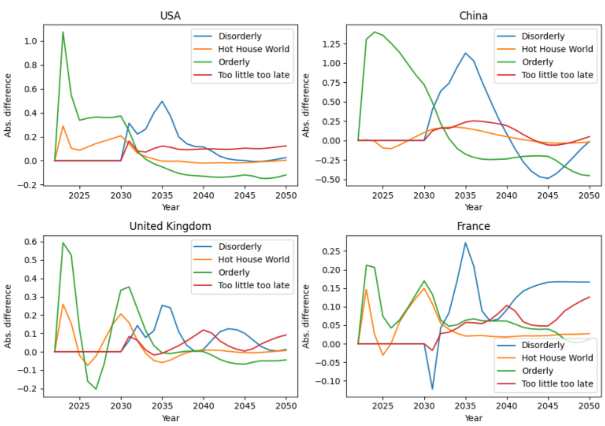


Figure 4: Evolution of GDP with combined risks

These graphs represent variations in GDP due to all risks, physical (chronic and acute) and transition risks. As such, they have a shape that seems to be a mixture of the previous forms. As we described earlier, in United States, United Kingdom and France, the orderly scenario has a very negative impact compared with the other scenarios in the first few years, and then this impact becomes better than that of the other scenarios. This is not the case in China where the impact is very similar to that of chronic physical risks, with the difference that the orderly scenario is less advantageous and the hot house world scenario is more advantageous.

The second variable we are interested in is the inflation rate.





Chronic physical risks

Transition risk

Figure 5: Evolution of inflation rate

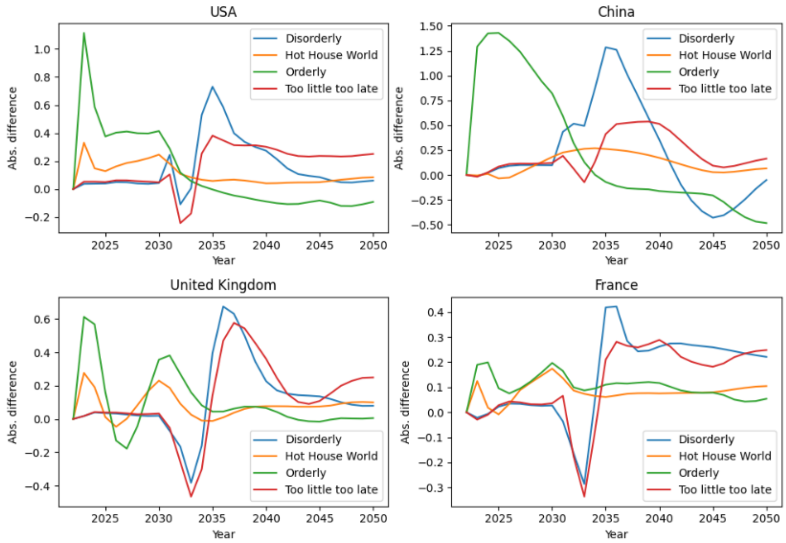


Figure 6: Evolution of inflation rate with combined risks

As far as chronic physical risks are concerned, the shape of the inflation rate curve is roughly the same for each country. We note that the most beneficial scenarios – those with the lowest inflation rates – are, in order, orderly, disorderly, hot house world and too little too late. There is also a clear long-term gap between the "orderly"/ "disorderly" group and the "hot house world"/ "too little too late" group. The first group even reaches negative inflation rates by 2050 in China.

Regarding the graph concerning transition risk and the one relating to combined risks, we observe that the orderly scenario leads to high levels of inflation in the initial years, but these levels decrease to often become negative in the following years. This scenario is the most beneficial in the long term. Conversely, the "too little too late" scenario results in either zero or low levels of inflation in the early years, but significantly higher levels in the longer term. This is the least favorable scenario in the long term.

2.2 Schiller database

To assess the long-term impact of climate risk in the financial sector, we need forward-looking data. This poses a significant challenge. In the literature, we've identified an indicator that tracks the measure of long-term stock market valuations : Campbell and Robert J. Shiller 1988 Cyclically-Adjusted-Price to Earnings ratio (CAPE).

2.2.1 The Schiller CAPE Ratio

In 1998, Robert Schiller and John Campell found that long-term equity market returns are not random walks and could be predicted through a measure they constructed: the Cyclically Adjusted Price–Earnings ratio (CAPE ratio). Schiller and Campbell calculated the CAPE ratio by dividing a long-term index of stock market prices and earnings (the index considered is the S&P 500 index) by the average earnings per share of S&P 500 companies over the last ten years, with earnings and stock prices measured in real terms. Then

$$CAPE_t = \frac{P_t}{[(EARN_t + EARN_{t-1} + ... + EARN_{t-10})/10]}$$

With P_t the stock market price and earnings level and $EARN_t$ the average earnings per share of S&P 500 companies.

2.2.2 Schiller's database and methodology

The Schiller database at our disposal contains monthly U.S. data on 19 variables from 1871 to 2023. These include the P_t value of the S&P index, earnings, dividends, the CAPE ratio, the annualized 10-year real return for the equity market and the same for the bond market. The 10 year annualized real return refers to annual returns over the next 10 years either on the stock market or on the bond market. They are observed over 10 years. This variable therefore refers to future or prospective returns. All these variables will be particularly useful in our study.

Schiller and Campbell adopt a methodology to relate the CAPE ratio to the level of forward equity market returns.

Shiller's CAPE methodology regresses the forward 10-year annualized real stock return (RET_t) on the current value of the CAPE ratio, over 1881–2004. They found:

$$\text{RET}_t = 0.270 - 0.177 \log\left(\text{CAPE}_t\right) + \varepsilon_t, \quad R^2 = 0.350$$

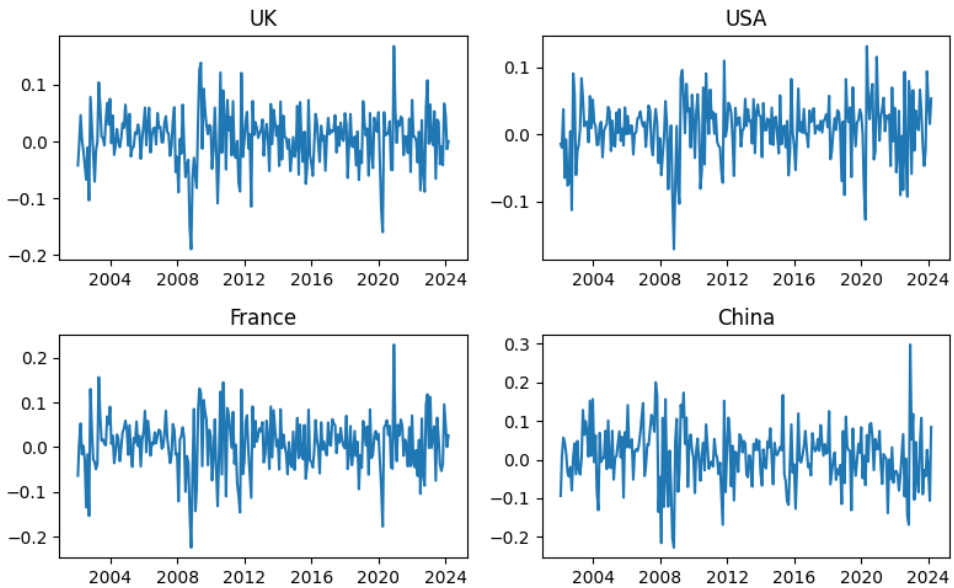
They obtained that the coefficient on the CAPE ratio is highly significant. Furthermore, the R^2 is 35%, indicating that the CAPE ratio explains more than a third of the variation of 10-year real equity returns. Using this regression, they are able to estimate and predict returns.

This methodology will be useful for us in our process of estimating how US equity expected returns are sensitive to shocks in GDP and Inflation.

2.3 MSCI data

The MSCI (Morgan Stanley Capital International) Index is a widely recognized benchmark for global equity markets. It provides investors with a comprehensive measure of equity market performance across various regions, countries, sectors, and market capitalizations. It therefore allows to assess international stock markets. Its capital international indices were the first global market indices for markets outside the US when they first became available in 1969. These indices include different categories to measure equity market performance in global developed markets, emerging markets, and frontier markets.

For our study, we utilized the monthly MSCI index data for four economies (United States, United Kingdom, China and France) spanning from December 2001 to February 2024. Figure 7 depicts the evolution of the variation of this index for each economy. A consistent average of the index is observed, with notable fluctuations occurring around crisis periods such as 2008 (real estate crisis) and 2020 (health crisis). The trend of the index appears to be similar across all four economies. Additionally, Figure 15 in the appendix displays the histogram of the variation in the MSCI index for these economies, indicating a distribution that appears to be normal with a mean closed to zero.



Source: Authors

Figure 7: Variation of the monthly MSCI index from January 2002 to February 2024

3 Analysis of sensitivity of returns

The aim of our study is to measure the impact of climate change on the equity market. Specifically, we will measure the impact of NGFS scenarios on prospective returns through macroeconomic variables. To do this, we already have at our disposal the shocked values of macroeconomic variables due to the different climate scenarios. We also need to estimate prospective returns in order to determine the sensitivities of these returns to the macroeconomic variables. We could then induce the various climate shocks on the macroeconomic variables to observe the behavior of the prospective returns.

At this stage of our study, we are proceeding with an analysis of the sensitivity of returns to macroeconomic variables. We use the Schiller database, which is, we recall, a database relating to the American market.

3.1 Estimation of prospective returns

We estimate prospective returns using the Schiller database and its CAPE ratio. The literature allows us to identify several estimators of returns. So, we acknowledge the following estimators of forward returns:

- The inverse of the CAPE ratio : $\frac{1}{CAPE}$
- Earnings to S&P Index value ratio: $\frac{E}{P}$ where E represents the average earnings per share of S&P 500 companies and P the value of the S&P index
- Dividend to S&P Index value ratio: $\frac{D}{P}$ where D represents the average dividend per share of S&P 500 companies;
- Returns estimated by regression: As Schiller did, we can run the following regression:

  $$\mathrm{RET}_t = \beta_0 + \beta_1 \log\left(\mathrm{CAPE}_t\right) + \varepsilon_t$$

  Where RET_t represents the forward 10-year annualized real stock return and the coefficients to be estimated. The result of the regression could then allow us to estimate prospective returns.

We will set up these estimations and compare them to determine the best one for our study. We can easily calculate the three ratios, since the variables are present in the Schiller database. Then, for the regression, The coefficients are significantly estimated on the training base by $\hat{\beta}_0 = \mathbf{0.2669}$ and $\hat{\beta}_1 = \mathbf{-0.0733}$ and $R^2 = \mathbf{0.3124}$. These results are similar to those of Schiller for the period 1881-2004, mentioned above.

We now calculate the mean squared error (MSE) of each of these estimators to give an indication of their reliability. We recall that the MSE is defined by:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(RET_i - \widehat{\text{RET}}_i)^2$$

To calculate the MSE for regression-estimated returns, we split the base into a test base and a training base. The training base is the one on which the regression has been trained, and the test base will provide us with the data that we will compare with the true values of the returns. For this reason, although the ratios are calculated on the whole base, we calculate their MSE on the test base in order to be able to compare the estimators. The MSE values obtained are shown in the table 2 below:

	1/CAPE	regressed returns	E/P	D/P
MSE	0.00176	0.00170	0.00193	0.00258

Table 2: MSE values of estimators

We notice that the forward returns estimated by regression seem to best represent the true forward returns, so we will use this method of estimating prospective returns for the remainder of this report.

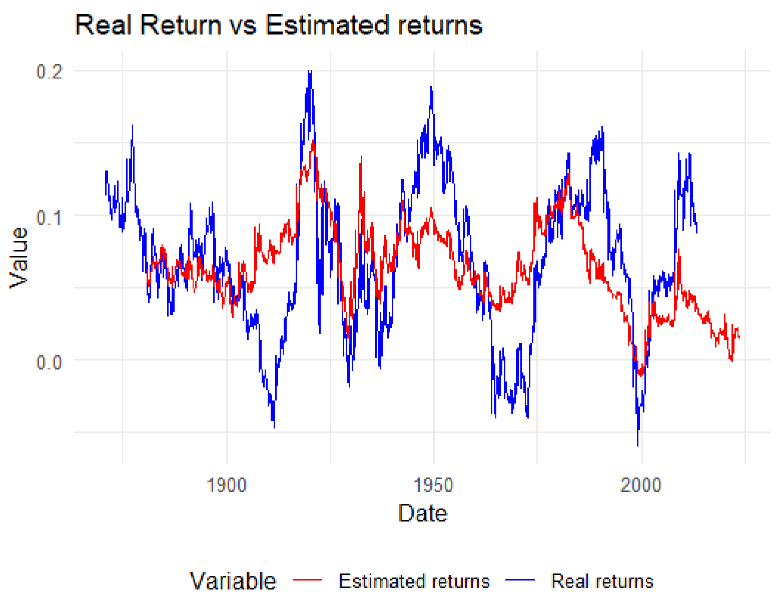


Figure 8: Real returns vs Estimated returns

This figure compares estimated returns with actual returns. We notice that the return estimator manages quite well to reflect the trends in the evolution of returns. Although there is often a time lag between the two curves.

The two graphs are not exactly over the same period. CAPE data are only available 10 years after the initial period, so estimated returns are only available 10 years after the initial period. On the other hand, actual returns are not available for the last 10 years, as the period has not yet been fully observed. We therefore realize that this method allows us to estimate future returns that have not yet been observed.

3.2 Analysis of sensitivities

We now proceed to analyze the sensitivities of estimated returns to macroeconomic variables. We retrieve publicly available US annual GDP data for the period 1970 to 2023.[3]

Our goal is to regress forward returns on macroeconomic variables. Since GDP data is annual and our estimated forward returns data is at a monthly frequency, we begin by taking the yearly average of estimated future returns. Given those prospective returns, we are now able to analyze the sensitivity of returns to macroeconomic variables such as gross domestic product (GDP). We are particularly interested in the growth of these variables over time. Therefore, we first estimate the following regression:

$$dERET_t = \beta_0 + \beta_1 * dGDP_t + \varepsilon_t$$

$ERET_t$ is the estimated prospective returns at time t and $dERET_t$ is its variation, i.e. $dERET_t = ERET_t - ERET_{t-1}$. And $dGDP$ is the GDP growth rate.

This regression gives us counter-intuitive results. The coefficients are estimated by $\hat{\beta}_0 = \mathbf{0.05}$ at a significant level and $\hat{\beta}_1 = \mathbf{-0.066}$ at a non significant level. The regression therefore suggests a negative relationship between GDP growth and forward returns. This implies that an increase in GDP of 1% leads to a decrease in the level of returns of 0.016. However, this regression and its results cannot be interpreted. Indeed, the coefficient is not significant, the regression is not globally significant and the Ljung Box test indicates an autocorrelation of the residuals.

[3] See https://fred.stlouisfed.org/series/GDPC1

We therefore try to estimate another regression including other variables. We supplement our data with publicly available annual US inflation data for the period 1970 to 2023.[4] The inflation rate corresponds to the percentage change in the CPI (Consumer Price Index). We now try to estimate the following regression :

$$dERET_t = \beta_0 + \beta_1 * dGDP_t + \beta_2 * d^2GDP_t + \beta_3 * dCPI_t + \varepsilon_t$$

d^2GDP is the second order percentage change in GDP and d^2CPI the second order percentage change in CPI.

We could first look at the relationship between the variables.

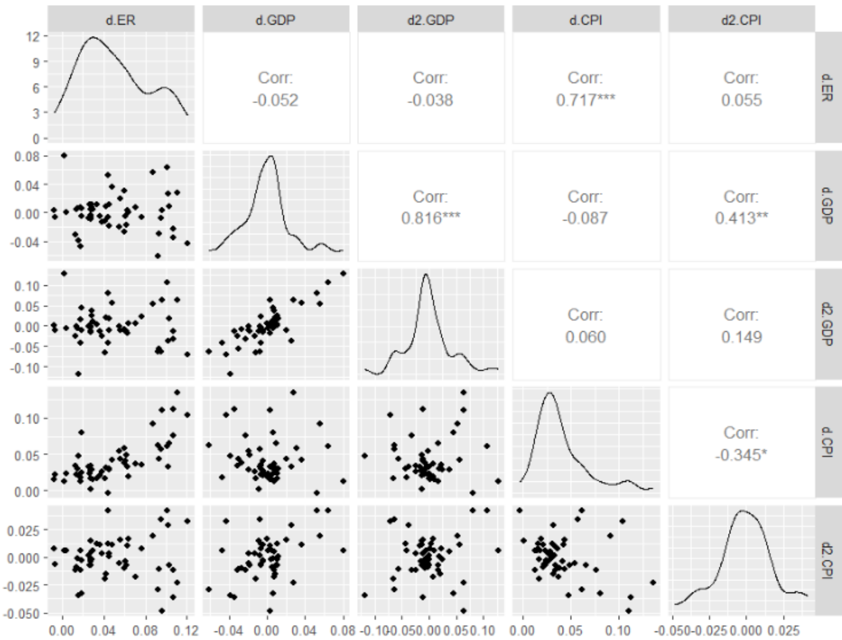


Figure 9: Relationship between regression variables

Only the first-order change in the consumer price index (CPI) appears to have a significant correlation with the target variable. Furthermore, this relationship seems to be represented by a linear relationship. This explains why we have kept only the first-order percentage change in the consumer price index in our regression. We do, however, introduce the second-order percentage change of GDP in order to capture possible non-linear effects.

The regression gives us the following results:

[4]See https://fred.stlouisfed.org/series/FPCPITOTLZGUSA

	Estimate	Std. Error	p value
(Intercept)	0.014	0.006	0.022
d.GDP	0.335	0.225	0.143
d2.GDP	-0.231	0.136	0.096
d.CPI	0.894	0.119	0.000

Table 3: Regression coefficients

So only the coefficient β_3 and β_0 are significant at the 5% level. But the other coefficients also have p-values close to 5%. This time, the β_1 coefficient of dGDP is positive, which is more intuitive. Thus, GDP growth evolves in the same direction as the variation of prospective returns. The second-order variation of GDP also appears to have a significant (negative) impact only at the 10% threshold on prospective returns. The regression is globally significant and the coefficient R^2 is worth **0.54**. This regression is much more better than the previous one.

3.3 Analysis limitations

A first limitation of this analysis is the estimation of prospective returns, which could possibly be improved. A second limitation is that we do not have the equivalent of Schiller data in the 3 other countries we are studying. We were therefore unable to reproduce this analysis for the other 3 countries (United Kingdom, France and China). Nevertheless, the Shiller et al. 2020'study, which explores the stock markets of the USA, Japan, China, and the United Kingdom, highlights the CAPE ratio's proficiency in forecasting long-term returns.

Given these limitations, our supervisors provided us their estimated sensitivities of prospective returns on the equity market. These sensitivities show the relationship :

$$dRET_t = 0.35 * dGDP_t + 0.35 * dCPI_t + \varepsilon_t$$

We assume that this relationship is valid in all 4 countries. It is this relationship that we will use to estimate the effect of climate scenarios on prospective returns.

4 Climate scenarios in prospective returns

At this stage of our study, we have a relationship between prospective returns and relative variations in GDP and in the consumer price index. We can therefore introduce the shocked values of these two variables according to the scenario. This gives us the evolution of the estimated variation of prospective returns over time.

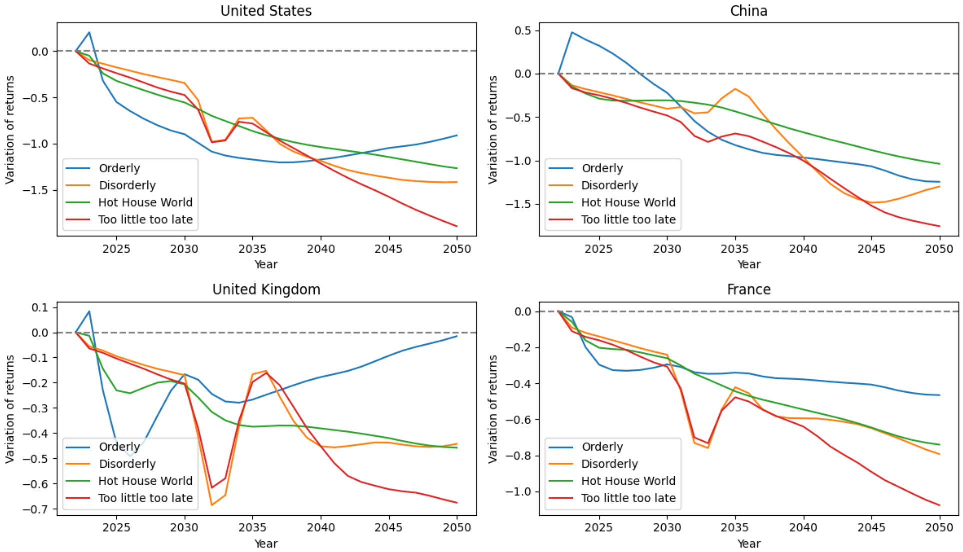


Figure 10: Evolution of the variation of prospective returns for all scenarios by country

We notice that the variation of returns is always negative, except in the early years, in some countries. This means that returns decline over time. In the USA, China and France, variations of returns are clearly on a downward trend, especially for the "Disorderly", "Hot house world" and "Too little too late" scenarios. For the "Orderly" scenario, the variation of returns picks up from 2040 in the USA and slowly decreasing from 2030 in France. In the United Kingdom, the negative effects are the least significant. Indeed, variations of returns are higher than in other countries, and the decline is less marked. Furthermore, the "Orderly" scenario, despite having a low peak in 2026, rises significantly thereafter until it is practically zero in 2050. It therefore seems that in this country and in this scenario, the climate policies adopted will quickly have a negative impact on returns, but will prove profitable in the longer term. Furthermore, in the UK, we notice a particular shape common to the graphs of the "Disorderly" and "Too little too late" scenarios. These graphs show a low peak in 2032, followed by a rapid rise to reach a high peak in 2036. These two scenarios are the ones with the highest transition risk. This effect is therefore possibly linked to this risk. A similar pattern can be seen in United States and France, but to a lesser extent.

Generally speaking, in United States, United Kingdom and France, the "orderly" scenario has the most negative effects in the early years, but quickly becomes the best-case scenario. On the other hand, the "Too little too late" scenario tends to merge with the "Disorderly" scenario in the early years, but becomes clearly worse than the latter around 2040. Since these two scenarios have approximately the same transition risk assumptions, we can deduce that this risk has a significant impact on the years up to 2040. Then, the high physical risk associated with the "Too little too late" scenario means that it ends up standing out from the "Disorderly" scenario. The case of China is different. Indeed, we can see that the "Orderly" scenario gives the best variation of returns until 2030, when it becomes less beneficial than the other scenarios, giving way to the "Hot house world" scenario.

5 Impact of climate change in Portfolio allocation

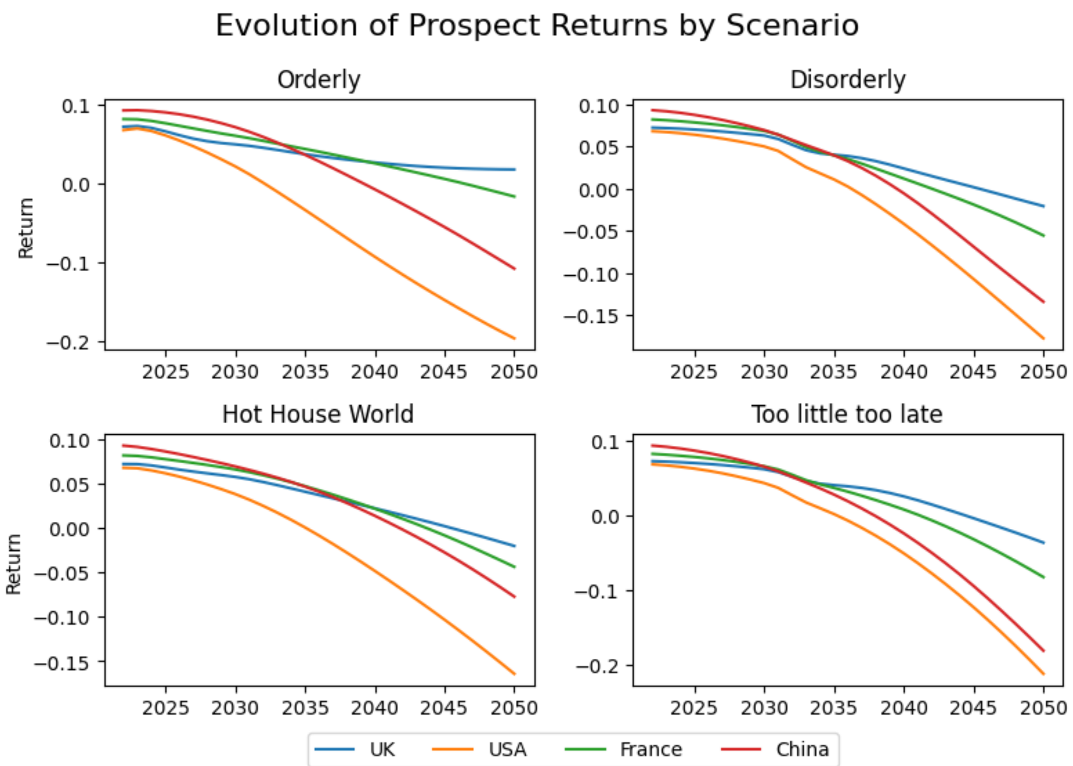


Figure 11: Evolution of prospective returns by scenario for all countries

In this part, we are looking at how climate change affects investing in the stock markets of the USA, China, France and United Kingdom.

Portfolio optimization is a useful approach to address this question. It involves solving a set of optimization problems to determine the best distribution of weights for the different assets in our portfolio. The objective is to maximize the expected return or profit from the portfolio while minimizing the risk involved. To integrate climate change considerations, we will employ two methods. Initially, we will maximize the Sharpe ratio to identify the optimal portfolio for each scenario, then we will use the Black-Litterman model.

The Black-Litterman model is particularly useful as it offers a structured method for incorporating individual investor's predictions about returns into the existing market data. In addition, this model tends to produce estimates that lead to more stable and diversified portfolios than those derived from historical returns when used with unconstrained mean-variance optimization. For these reasons, we will employ the Black-Litterman model in our portfolio allocation approach.

5.1 Sharpe ratio maximization in portfolio allocation

5.1.1 Methodology

The Sharpe ratio is defined for each asset in the portfolio by :

$$\text{Sharpe Ratio} = \frac{R_e - R_f}{\sigma_e}$$

Where :

- R_e is the expected return of the asset;
- R_f is the risk-free rate;
- σ_e is the annual volatility of the asset.

It describes the excess return you receive for holding a riskier asset.

The issue we are addressing is referred to as the max-Sharpe problem. It involves maximizing the Sharpe ratio without considering the risk-free rate denoted by R_f. The Sharpe ratio is defined as the ratio between the expected excess return of an asset and the square root of its variance.

From theoretical viewpoint, given a set of n assets, let $\mu = (\mu_1, \ldots, \mu_n)$ be the vector of expected returns of such assets and $\mathbf{w} = (w_1, \ldots, w_n)$ be a weight vector such that $\sum_{i=1}^{n} w_i = 1$. The total expected return of the portfolio is calculated as the weighted sum of the expected returns of each asset, i.e., $\mathbf{w}^T \mu$.

The risk or volatility of the portfolio is quantified by the standard deviation, denoted as σ, which is the square root of the portfolio variance. The portfolio variance is computed as the quadratic form of the weight vector and the covariance matrix Σ, i.e., $\mathbf{w}^\top \Sigma \mathbf{w}$. For an in-depth treatment of Portfolio Optimization techniques one can refer to (Cornuejols and Tütüncü 2006).

The problem is therefore formulated as :

$$\begin{aligned} &\max \frac{\boldsymbol{w}^T \boldsymbol{\mu}}{\sqrt{\boldsymbol{w}^T \Sigma \boldsymbol{w}}} \\ &\text{s.t. } \sum_{i=1}^{n} w_i = 1 \\ &\quad\quad w_i \geq 0 \quad \forall i = 1, \cdots, n \end{aligned}$$

5.1.2 Portfolio allocation

We will now apply the methodology described to estimate the optimal weights to allocate to each of the assets in our portfolio. In our case, the portfolio is made up of the 4 countries whose historical performances are based on MSCI data from 2002 to 2022. Our goal is to find the optimal portfolio at each date, from 2022 to 2040.

In practice we need to estimate the expected returns and the matrix of variance covariance of the assets. To estimate the expected return, we assume a long term Sharpe ratio of 0.25 during the initial year (2022) and a long term US Cash rate of 3%. We consider this cash rate to be the risk-free rate for all countries. We utilize the Sharpe ratio to estimate the returns in the initial period using the formula:

$$R_e = \text{Sharpe Ratio} \times \sigma_e + \text{Cash rate}$$

The variance-covariance matrix Σ (Table 6) is calculated using the MSCI data and the σ_e is the square root of the main diagonal of Σ. So we calculate the returns for the initial year 2022, using the Sharpe ratio. Then, for subsequent years, we obtain the expected returns by adding to the last return the variation in returns we found in section 4. The expected returns are rpresented in figure 11. These expected returns then allow us to find the optimal portfolio allocation by solving the optimization problem.

Figure 12: Evolution of the portfolio allocation over time using sharpe ratio maximization

The initial portfolio allocation, common to each scenario, is given by:

Country	Expected returns (%)	weight
UK	7.25	0.159
USA	6.82	0.554
FRANCE	8.22	0.000
CHINA	9.33	0.287

Table 4: Portfolio allocation in 2022

The figure 12 shows that this allocation evolves differently depending on the scenario. The weights obtained must always sum to 1, for each year and in each scenario.

In the orderly scenario, China becomes the majority asset from 2025 onwards, and even monopolizes investment between 2030 and 2036. However, from 2039 onwards, it becomes more profitable to invest in the UK. This seems logical, since in this scenario, as we noted earlier, China had the highest returns from 2022 to 2035, while the USA, for example, was already experiencing negative returns. After 2036, China's returns fall drastically, leaving the way open for France and, above all, the United Kingdom.

In all scenarios, we can see that the weight associated with the United States decreases, then cancels out before 2030. This is due to the fact that the associated returns quickly become negative. This pattern is also found for France and China in the "Too little too late" scenario. In this scenario, the weights associated with the three countries decrease and cancel out before 2034, with the UK taking all the investment. France's weight is almost always zero, except in the hot house world scenario, where it is the majority asset between 2027 and 2037. It should be noted that France's initial weight is zero. It is therefore difficult to achieve significant weights in this context of decreasing returns.

It is clear from these results that portfolio allocation is very different from one scenario to the next. This highlights the significant effect of climate risk on asset allocation. In all scenarios, the weighting associated with the UK increase over last years. This indicates good long-term climate risk management in the UK, compared to other countries in the portfolio.

5.2 The Black-Litterman model

5.2.1 The Black-Litterman methodology

There are several improved versions of the Black-Litterman model that overcome limitations of the original approach, like the assumption that market data fit into a normal distribution. Here, we will introduce short presentation of the canonical Black-Litterman reference model, which is widely used in the literature and easy to implement in various software such as MATLAB and Python.

First, we start with normally distributed expected returns

$$r \sim \mathcal{N}(\mu_{eq}, \Sigma) \tag{1}$$

Secondly, we calculate the variance-covariance matrix Σ from market data. This allows us to estimate equilibrium returns μ_{eq} derived from CAPM (Capital asset pricing model) equilibrium theory by inverse optimization: $\mu_{eq} = \gamma_M \Sigma x_M$ where x_M denotes the market portfolio (tangency portfolio of the mutual fund theorem[5]) and γ_M is the known market risk aversion. Third, we need to specify the k investor's views represented by:

1. P, a $k \times n$ matrix of the asset weights within each view. n refers to the number of assets.

2. V, a k×1 vector of the returns for each view.

3. And Q a diagonal $k \times k$ matrix of the covariance of the views expressing the uncertainty in the forecast.

[5] The mutual fund theorem is an investing strategy whereby mutual funds are used exclusively in a portfolio for diversification and mean-variance optimization

Finally, we use Bayes theorem for the estimation model :

- prior: $R \sim \mathcal{N}(\mu_{eq}, \Sigma)$,
- observation: $V \mid R = r \sim \mathcal{N}(Pr, Q)$.

The posterior distribution of future returns R given $V = v$ is given by the Bayes formula

$$f_{R|V=v}(r) \propto f_{V|R=r}(v) f_R(r)$$

and is normal with mean

$$\mu_{BL} = \mu_{eq} + \Sigma P^T (Q + P\Sigma P^T)^{-1} (v - P\mu_{eq})$$

and covariance matrix

$$\Sigma_{BL} = \Sigma - \Sigma P^T (Q + P\Sigma P^T)^{-1} P\Sigma.$$

In the market-based Black-Litterman approach, these values are directly applied in portfolio optimization in the mean-variance setting.

For more technical details, you can check out the work of these two authors: (Walters 2011) and (A. Palczewski and J. Palczewski 2019).

In practice, at minimum a Black- Litterman oriented investment process would have the following steps :

- Determine which assets constitute the market
- Compute the historical covariance matrix for the assets
- Determine the market capitalization for each asset class.
- Use reverse optimization to compute the CAPM equilibrium returns for the assets
- Specify views on the market
- Blend the CAPM equilibrium returns with the views using the Black-Litterman model.

5.2.2 Estimation of the model in each scenario

We will use MSCI index data to estimate the historical covariance matrix for the assets. The market capitalization (Table 5) of each asset can be easily found in the msci site web[6].

[6] MSCI CHINA, MSCI FRANCE, MSCI USA, MSCI UK

Country	**Market Capital ($)**
UK	2 376 209.91
USA	44 943 197.19
FRANCE	1 846 352.62
CHINA	1 816 377.30

Table 5: Market Capitalization of different Countries

We use the closing prices of the S&P500 (We suppose here that S&P represents the global market) to estimate the level of risk aversion γ_M among market participant.

Specifying the views is not straightforward and varies depending on the investor. We employ a simple methodology to address this, which we will describe below. We will base our analysis on the projected return results (refer to section 5.1.2 and figure 11). Our analysis will focus on the year 2035. In this section, we will detail our views for the orderly's scenario. For the others scenarios, please refer to the appendix.

Views on the orderly scenario

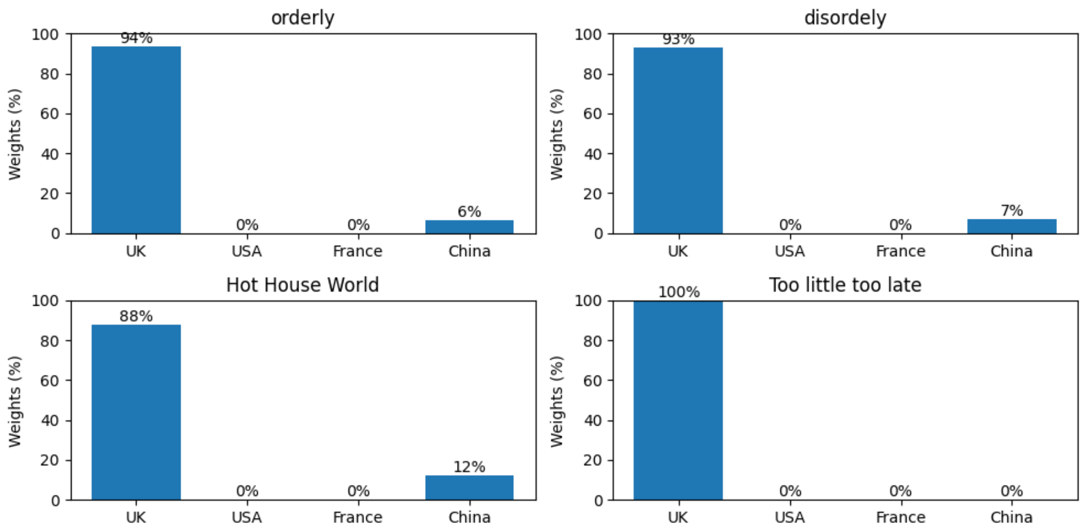
The selection of views will depend on the investor's risk preference, that is, whether he is risk-seeking or not. We will provide a simple illustration of choosing views in 2035:

- MSCI index France will outperform MSCI index UK by 0.007 percentage point with high confidence. This is a relative view.
- MSCI index UK will outperform MSCI index China by 0.007 percentage point with high confidence.
- MSCI index China will outperform MSCI index USA by 0.07 percentage point.

We can specify those views by matrix. Here, we only have relative views. For a relative view the sum of the weights will be 0, for an absolute view the sum of the weights will be 1.

$$P = \begin{bmatrix} 0 & 1 & -1 & 0 \\ -1 & 0 & 1 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix}, \quad Q = \begin{bmatrix} 0.007 \\ 0.007 \\ 0.07 \end{bmatrix}, \quad \Omega = \begin{bmatrix} w_1 & & \\ & w_2 & \\ & & w_3 \end{bmatrix}$$

Where $w_i = 1$ for $i \in \{1, \ldots, 3\}$ for high confidence. The values in the confidence matrix range from 0 to 1, where 0 indicates a low level of confidence in the view, and 1 indicates a high level of confidence. For the others scenarios, one can refer to the appendix to obtain the views.



Source: Authors

Figure 13: Portfolio allocations by scenario in 2035 using black-litterman model.

Unlike the previous model, in this model we have only optimized the portfolio for the year 2035, as we would have had to specify the views for each year. We can see in figure 13 that, whatever the scenario, the UK represents the majority asset. So, once again, we can see that the UK is more resilient to climate risk than the others economies. On contrary, the weights associated with the United States and France are zero, whatever the scenario. These results are similar to those observed in 2040 with Sharpe maximization, but slightly less similar to those observed in 2035 with Sharpe maximization.

Conclusion

In this paper dedicated to analyzing the impact of climate change on strategic asset allocation, we first describe the evolution of macroeconomic variables (GDP and CPI) according to different climate scenarios in four regions. Then, we estimate prospective returns to determine the sensitivities of these returns to macroeconomic factors. Afterward, we introduce various climate shocks to observe the behavior of prospective returns. Finally, we integrate climate change into portfolio allocation using two methodologies: the Sharpe ratio and the Black-Litterman model.

To accomplish this, we utilized several databases, including NGFS data for climate scenarios, Schiller data for forward-looking returns estimates in the US, and MSCI indices to estimate the historical covariance matrix for the assets.

Our analysis indicates that asset managers would be prudent to consider climate risk when allocating their assets. Additionally, we observe that prospective returns decrease across all scenarios, with the "too little too late" scenario exhibiting the most significant decline. While the orderly scenario may present short-term disadvantages due to policies aimed at achieving a low-carbon economy, it offers long-term advantages.

The difficulty of this study was access to data, in particular access to forward looking data on all the countries we studied. For this reason, we have estimated prospective returns. However, this represents a major limitation of our study. In addition, the estimation of prospective returns, could benefit from refinement and enhancement. Another limitation is the aggregation of NGFS data. We have aggregated models and scenarios. It might be interesting to work on each model and consider the 7 NGFS scenarios at a disaggregated level.

An extension to this study could be to find a methodology for assigning probabilities of occurrence to each of the NGFS scenarios. In this way, we could create an allocation strategy combining the various NGFS scenarios, weighting each scenario by its probability of occurrence.

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Glossary

Asset	:	Anything of value owned by an individual, institution or economic agent, that can be traded on a financial market.
Assumptions	:	Accepted premises used in modeling.
Back-testing	:	Assessing climate models using past data.
Bayesian inference	:	Statistical approach that quantifies uncertainty by updating beliefs about unknown parameters using prior knowledge and observed data.
Climate	:	Succession of weather conditions in a given place over a long period of time.
Climate models	:	Tools simulating future climate scenarios.
Climate-related risks	:	Dangers linked to climate change's effects on various systems.
Climate risk	:	Loss of financial value of an asset due to climate change.
Covariance matrix	:	Summarizes the relationships between multiple dataset.
CPI	:	A weighted average of the prices of a representative market basket of goods and services that represents consumption patterns in some base time period.
Forward-looking data	:	Information predicting future climate conditions.
Economic variables	:	Factors affecting financial conditions.
GDP	:	Gross Domestic Product: The market value of all final goods and services produced in a given time period.
Inflation	:	Widespread, self-sustaining increases in the market price of goods and services.
Investment returns	:	Profits or losses from investments.
Investor's view	:	An investor's perspective on the market.

Low-carbon economy	:	Economic activities that deliver goods and services that generate. significantly lower emissions of greenhouse gases; predominantly CO2
Macroeconomic	:	Study of the national and international economy.
Model	:	Simplified representation of reality.
Physical risk	:	Climate risk relates to the direct impacts of climate change on the economy such as extreme weather events, sea-level rise, and change in temperature and precipitation patterns.
Posterior	:	Reflects the updated beliefs about the parameter after incorporating observing data through Bayesian inference.
Prior distribution	:	Represents existing knowledge or believe about an uncertain parameter before observing data.
Random variations	:	Unpredictable fluctuations in data.
Risk Averse	:	Behavior by economic agents who have a preference for avoiding or minimizing risk.
R^2	:	Proportion of target variable variability that is explained by the model.
S&P500	:	Measure that track the performance of 500 leading publicly traded companies in the US.
Scenario	:	Probable economic event or Hypothetical situations used for analysis.
Stochastic	:	Random or unpredictable in nature.
Stress testing	:	Analysis or simulation designed to determine the ability of a given financial instrument or institution to deal with an economic crisis.
Transition risk	:	Climate risk relates to the effort to mitigate climate change and adapt to its impacts, such as changes in policy, technology.

Appendix

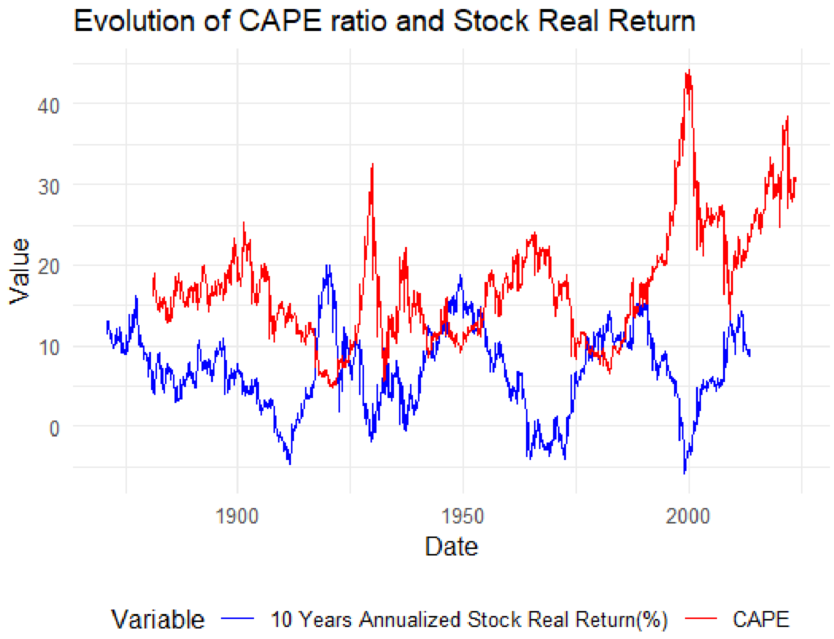
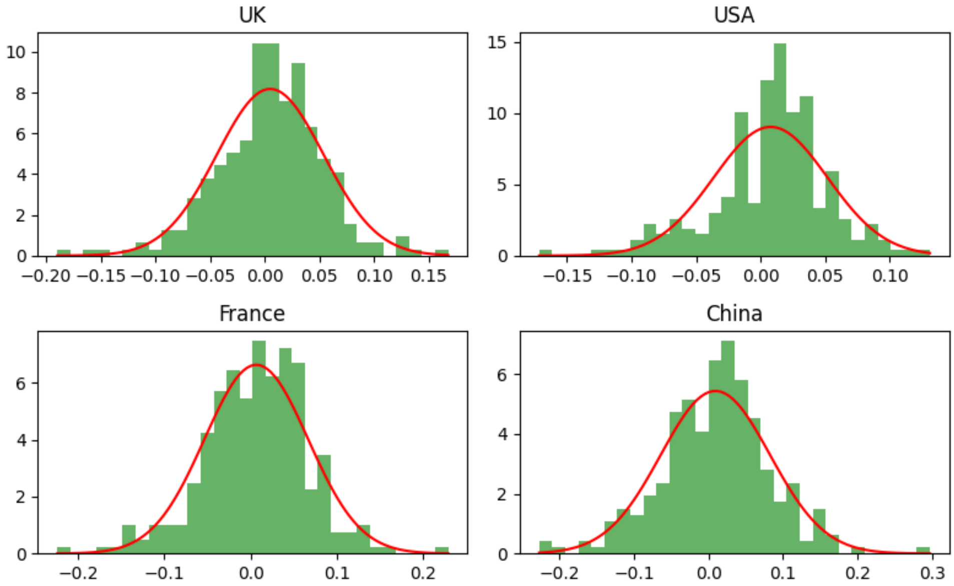


Figure 14: CAPE ratio

	UK	USA	France	China
UK	0.029	0.022	0.033	0.026
USA	0.022	0.023	0.027	0.020
France	0.033	0.027	0.044	0.030
China	0.026	0.020	0.030	0.064

Table 6: Covariance matrix of Monthly MSCI index



Source: Authors

Figure 15: Histogram of MSCI index

Views on Disorderly

- MSCI index UK will outperform MSCI index France by 0.001 percentage point with confidence w_1.
- MSCI index France will outperform MSCI index China by 2.69×10^{-5} percentage point with confidence w_2.
- MSCI index China will outperform MSCI index USA by 0.028 percentage point with confidence w_3.

Views on Hot House World

- MSCI index France will outperform MSCI index China by 0.0005 percentage point with confidence w_1.
- MSCI index China will outperform MSCI index UK by 0.0057 percentage point with confidence w_2.
- MSCI index UK will outperform MSCI index USA by 0.040 percentage point with confidence w_3.

Views on Too little too late

- MSCI index UK will outperform MSCI index France by 0.0037 percentage point with confidence w_1.

- MSCI index France will outperform MSCI index China by 0.008 percentage point with confidence w_2.
- MSCI index China will outperform MSCI index USA by 0.026 percentage point with confidence w_3.