THE ROLE OF POLICY UNCERTAINTY IN SHAPING INVESTMENT DECISIONS

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COURSE IN CLIMATE AND TRANSITION RISKS: UNCERTAINTIES, COMPLEXITY, AND IMPLICATIONS FOR ECONOMIC AND FINANCIAL DYNAMICS

Contents

1. ACADEMIC OUTLOOK

1.1 INTRODUCTION TO REGULATORY UNCERTAINTY AND ITS FEATURES

Price uncertainty is one of the main variables of risk that companies must face, and the one related to CO2 price may at first appear limited. Nevertheless, there are features of CO2 price that must be considered; one of them is the fact that it depends on emission trading and climate policy. Since they are widely subject to regulatory uncertainty, also CO2 price's impact on the proficiency of an investment becomes more relevant and unpredictable.

The regulation establishes at what level of stringency and under what rules CO2 markets (ETS) and other policy instruments are implemented; in other words, it will have an impact on carbon price. In fact, policy uncertainty is modelled as a discreet jump in price at some known time in the future resulting from a policy announcement that might arise at the beginning of a new allocation period in an emissions trading scheme, or the announcement of a new tax rate, technology standard or other regulatory approach.

Hence, the issue is how to assess regulatory uncertainty before making an investment despite all the obstacles around it: first, regulatory uncertainty is driven by rather soft factors relating to future decisions by policy makers. These are difficult to quantify, therefore it is difficult to attribute probabilities to different scenarios.

Second, climate policy has international objectives and involves activities by many nations. The evolution of such non-corporative games is particularly difficult to predict as frequently multiple outcomes are feasible. Furthermore, if climate policy is implemented only in part of the world, then leakage can influence certain sub-sectors. Again, these distortions are difficult to quantify and predict and puts additional pressure on policy makers: the additional uncertainty complicates investment choices or creates additional costs for capital (risk premiums).

1.2 RISK PREMIUMS AND POLICY UNCERTAINTY

First off, risk requires net returns to be higher than would be necessary where there was no uncertainty. This higher net return is called the "risk premium" for either fuel price uncertainty or carbon price uncertainty. The risk premiums depend on the technology being considered, the market context in which the company operates, and the details of the climate change policy mechanism being considered of which this essay will focus on.

Let's consider the type of risk premium associated with uncertainty for an existing or a proposed new policy. These risk premiums are derived from a consideration of the flexibility that companies have in deferring investment and waiting for additional information that could improve the outcome of their investment decision.

For all technologies, both emission and non-emission intensive, the climate change policy risk premium depends on how long there is left for the policy to run. The fewer the number of years remaining until an expected change in policy, the greater the risk premium associated with policy uncertainty. This assumes that there is no visibility at all about future climate policy before the end of the existing policy.

Figure 1 shows the risk premiums in terms of additional capital investment costs (USD/kW) that are associated with uncertainties of energy price and carbon price.

The results indicate that climate policy risks may be brought down to modest levels compared to other risks if policy is set over a sufficiently long timescale into the future.

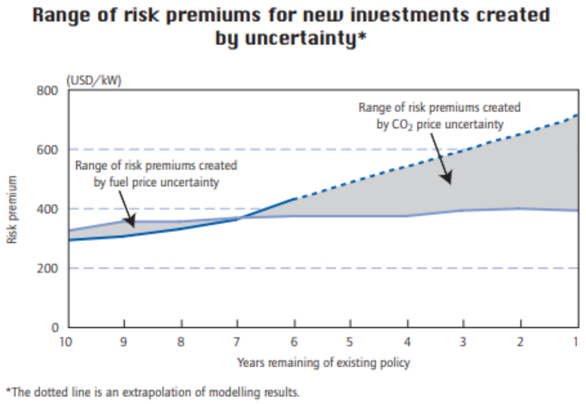


Figure 1 - Risk premium and policy uncertainty

1.3 UNCERTAIN TIMING FOR POLICY INTRODUCTION AND OPTION VALUE TO WAITING

This leads us to the importance of timing for policy introduction and the option value to waiting.

Uncertain timing of climate policy could be modelled by estimating a best guess (expectation value) of when the policy might be introduced, and then estimating a range for the earliest and latest likely introduction dates.

Let's consider the case of two types of plants, one with a low-carbon impact and the other more emission-intensive. Imagine that if climate policy is introduced at the expected time, the economic case over the plant lifetime for the two projects is the same.

However, the risks will be opposite: an earlier than expected introduction of climate policy would be beneficial to a low-carbon emitting project, whereas a later than expected introduction of policy would be beneficial for unabated coal and other more emissions-intensive plants, as shown in figure 2.

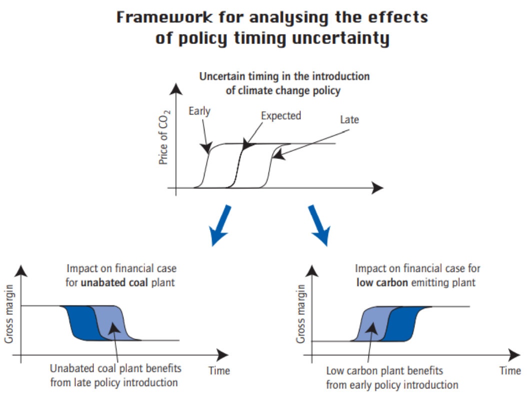


Figure 2 - impacts of policy timing uncertainty

This result confirms that the effects of policy uncertainty are conditioned to the technology being considered.

For what concerns uncertain policy timing, there will be an option value to waiting if waiting yields better information about when policy will be introduced. It is quite likely that waiting could yield useful information to the investor. For example, it might allow the tracking of new laws through the legislative process and allow companies to accept and manage the results of government review processes.

There may also be an inherent value to waiting simply by virtue of the passage of time once the initial estimate of the earliest introduction date has been passed. In that case, each year that passes without introduction of a policy would reduce the range between earliest and latest introduction dates.

The value of waiting could be reduced if policy makers send clearer signals to companies about the likely timescales for policy introduction. This suggests that in situations where there is currently no stated climate change policy, the introduction of timetables and targets for future policies will help reduce the risks for companies planning investments.

2. WORLD BANK AND FED OUTLOOK

In this section of the paper, discussions about how the global authorities worked on the topic will be made. In the study conducted by Fried et al. (2021) for the Federal Reserve Board of the United States, they have mentioned about the macro effects of climate policy uncertainty. According to the paper, although the US government has not introduced a federal price on carbon emissions yet, it is seen highly likely to introduce a policy by them. With the help of mathematical models, Fried et al. (2021) reached a conclusion that even the policy risk directs the economy in a greener production as if the US government introduced a federal tax of $3.21/ton of CO2. Therefore, it can be said that, at the period of time where the policy has not been introduced yet, in other words period of time where there is an uncertainty, the action takers such as producers tend to invest in finding alternatives that could replace current systems with a system that could comply with the possible future policies.

Risk aversion is one of the main amplifiers of why action takers shift to green alternatives. They have to weigh the outcomes of both cases where climate policy is introduced or not. Considering the possibilities, investors have to hedge against lowest utility where a climate policy is introduced. To be affected less, they should start investing in greener alternatives for their businesses before the climate policy is introduced.

Naturally, one would expect delays in the introduction would cause an increase in the environmental costs. However, climate policy risk and risk aversion causes relatively lower costs. Furthermore, in the study of Hallegatte et al. (2012) for the World Bank, it is suggested the investment projects which are conducted under deep uncertainties, have to be robust. A model can be defined as robust, if the results do not face a significant change even the inputs are variable. For instance, in the figure below, possible changes according to two different models for the annual rainfall in 2080-2100 with respect to the 1980-2000 period in Africa can be seen.

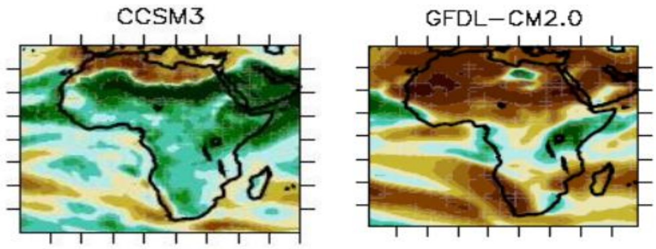


Figure 1. Annual rainfall in 2080-2100 in Africa by different models

One investor who is planning to invest in the area cannot disregard one of the two models that gives a result completely inverse from the other one. The model or the system that the investor will construct, should comply with both cases if the investment is irreversible and untransformable.

In some cases the optimal solution which is found by cost-benefit analysis may not comply with the robust solution since the optimal solution is found under specific conditions and constraints and it gives the result that provides the most benefit, yet robust solution may not be the optimal one. In such cases, investors should use a mix of these strategies when deciding on their investments. At this point, the expected time to utilize the investment is also important. If the investment is intended to be utilized for a shorter period of time where the levels of uncertainty are relatively lower, then investors could continue with the optimal. Unlikely, if it is expected to have a longer lifespan, robust solutions could be applied to sustain the continuity of the investment with higher uncertainty. Likewise, downscaling for projection of climate variables is mostly carried out to reduce the effects of uncertainty. It is better to rely on data and results that already exist.

3. EMPIRICAL CASE

In the research made by Ren et al. (2022), the effects of uncertainties on investment decisions of the companies which operate in the energy sector in China are discussed. With the increasing attention given to climate risks in recent years, climate policies of the world and countries individually change rapidly which causes an uncertainty that affects the investment decisions of the companies. This study gives us an excellent overview about the subject. With the help of panel data of 128 Chinese companies which operate in energy-related sectors, the study builds a dynamic threshold model.

Corporate investment is one key element which constructs the future of a specific company by deciding on the future organization, product portfolio, strategy. The decision on corporate investment has to be done considering the external factors such as the sectoral condition, input prices, regulations that are implemented by the authorities and many more others. Although it is a fact that the authorities have to implement climate policies in order to control the companies' negative effect on the climate, it is relatively hard to come up with the optimal levels for the companies to carry on their economic activities with minimal damages. Energy sector would be the most affected by the changing climate policies on the first thought since most of the current world's energy production is made through fossil fuels, coal which causes carbon emission at highest levels compared to other industries. Furthermore, China is an important country that should be worked on since with the industrialization moves, they became one of the largest emitters. With emerging facts countries tend to adopt more intolerant policies for carbon emission such as carbon taxes which have a significant effect on corporate investment.

If the investment project is hardly reversible, decision makers tend to wait for thorough analysis and optimal time. The research from Appelbaum and Katz (1986), suggested that if the level of risk aversion is high, companies are less likely to invest and produce. On the contrary, Abel (1983) suggested that if the ability of the company to deal with uncertainty is high, they are more likely to see the uncertainty as an opportunity to invest more to maximize their returns. According to Phan et al. (2021) larger companies have more possibility to be affected more from policy uncertainty since they could be less agile while adapting.

Main result that can be interpreted from the study of Ren et al. (2022) is that policy uncertainty has various effects on different sectors. Coal mining in China provides the main input for energy production. Since usage of coal is one of the main reasons for carbon emission, when a stricter climate policy is introduced, the firms that operate in this area would be the first to be affected. On the contrary, companies which operate in production of natural gas, electricity, and oil, are expected to be less affected since they are more involved in daily lives of the people in the short period. Furthermore, in the long run, these companies could increase their investment levels to shift their operations in more eco-friendly ways when new climate policies are introduced.

4. PROFESSIONAL OUTLOOK

By attempting to offer a diverse and more pragmatic point of view, we have researched, through various Investment banks' research and letters to investors, what can be considered as the industry outlook to climate-related policy uncertainty.

Elevated volatility can make staying invested in the markets challenging for investors.

Behavioral biases can manifest themselves throughout a market cycle. They can be especially pronounced during crises when emotional responses are heightened. Investors typically feel a predictable series of emotions during the cycle making it easier to get invested when markets are rising, but may also induce selling during downturns.

Figure 2: Market cycle emotions
Typical emotions felt by investors at various stage of the market cycle from boom to bust

Source: Barclays Private Bank

Periods of heightened uncertainty, volatility and falling markets can trigger fear and panic and the first instinct of investors may be to sell or reduce risk. Holding falling assets, combined with uncertainty over when the bottom will be reached, can take a toll on investors. This is a natural response; when your portfolio is at risk, your long-term goals are too.

4.1 ON CLIMATE CHANGE

JP Morgan's Asset Management team has repetitively expressed their positive beliefs in the possibility of mitigating the risks of climate change by constructing their equity portfolios to be "transition ready."

Even though, assuming governments take some action to address climate change, the drag on corporate profitability may lead to a modest fall in average equity valuations of around 3%.

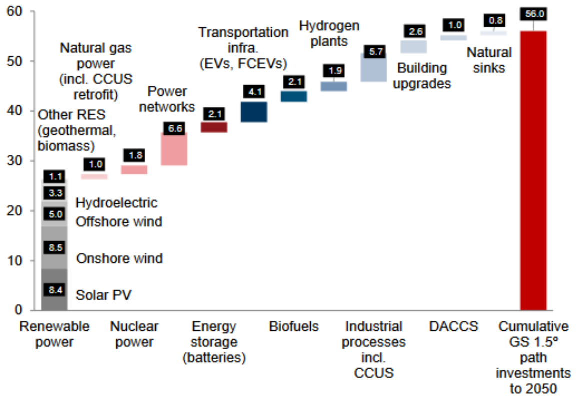
There are several plausible counterbalances, however. Insulating economies from exogenous oil price volatility may feed through to lower macroeconomic volatility and thus reduce equity risk premia (supporting equity valuations). Similarly, the level of interest rates and the types of fiscal policy enacted will affect equity valuations over a 10- to 15-year investment horizon.

Goldman Sachs's Global Macro Research team has published an interesting report on investing in climate change 2.0.

They show the path to net zero in relationship with the investments by using these two interesting pics:

~$56tn of investment needed for global Net Zero carbon

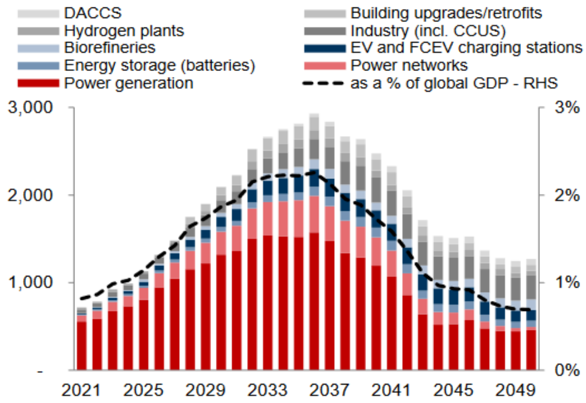
Cumulative infra. investment in GS 1.5 °C net zero model, $tn



Note: Represents cumulative total figure for global investment by 2050.
Source: Goldman Sachs GIR.

Investment to reach >2% of GDP by 2032 in 1.5°C scenario

Ann. infra. investment for net zero by 2050, $tn; as % GDP (rhs)



Note: This only reflects incremental investment and doesn't include maintenance/other capex.
Source: Goldman Sachs GIR.

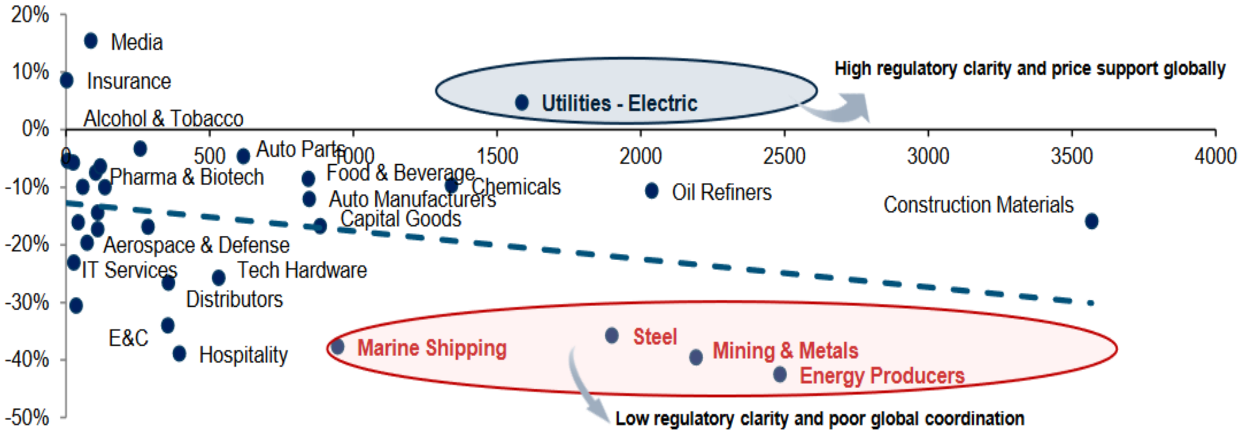
As well explained by Michele Della Vigna, Head of Energy Industry Research at Goldman Sachs, the mismatch between the limited reach of global decarbonization policies and carbon pricing on one hand and the deep structural change in global capital allocation on the other is driving a two speed de-carbonization process that is severely constraining capital allocation to hydrocarbons and other high-carbon sectors like heavy transport and materials while the development of low carbon alternatives is not yet properly incentivized.

These dynamics have led to structural underinvestment in key parts of the economy—energy, materials, and heavy transport sectors are all reinvesting around 40% less of their cash flow on average vs. the 10-year average. Policy uncertainty is at the core of this underinvestment.

This structural underinvestment in high-carbon sectors is likely to drive commodity prices higher over the medium-to-longer term, raising affordability concerns, but also increasing the relative attractiveness of de-carbonization technologies.

Shareholder pressure and lack of policy coordination have led to structural underinvestment in key parts of the economy

Carbon intensities (scope 1, 2, 3 emissions)/revenue (x-axis, tonCO2eq/$mn) vs. reinvestment ratio (2022E vs. 10yr avg) (y-axis, %) (data excludes 2020)



Source: Company data, Goldman Sachs GIR.

Jeff Currie, Global Head of Commodities Research at Goldman Sachs, argues that the lack of a global carbon price/tax has led to fragmented local climate policies and ESG investing in suboptimal and green inflationary solutions for tackling climate change.

He believes that the inability to create a globally coordinated policy response has also given rise to ESG investing, which in itself creates new market failures. While ESG investing raises the cost of capital for emitter firms and reduces it for green enterprises, resulting in higher hydrocarbon prices that act as a carbon price or tax, it fails to collect any revenue raised through a tax. And the "tax revenue" from higher oil, gas and coal prices in the form of profits, dividends and share buybacks goes to the emitters and to countries like Russia and Saudi Arabia that produce hydrocarbons.

Furthermore, the excess capital now going to green investments will ultimately lead to overinvestment and poor returns in these sectors.

Even though the explosion of ESG funds has to be considered due to social reasoning by the investors, they are still driven by profit and the desire to make money out of their investments.

But tackling climate change is likely the most expensive endeavor humans have ever consciously undertaken. The scale of de-carbonization investment required for the new green economy is becoming increasingly clear: an extra $2.8tn/year, equivalent to China's entire 2000's investment, for a total of $6 trillion per year this decade.

With such a large amount of capital needing to be deployed, the lack of an effective policy framework to channel those investments represents a structural risk to the long-term value of ESG investments this decade.

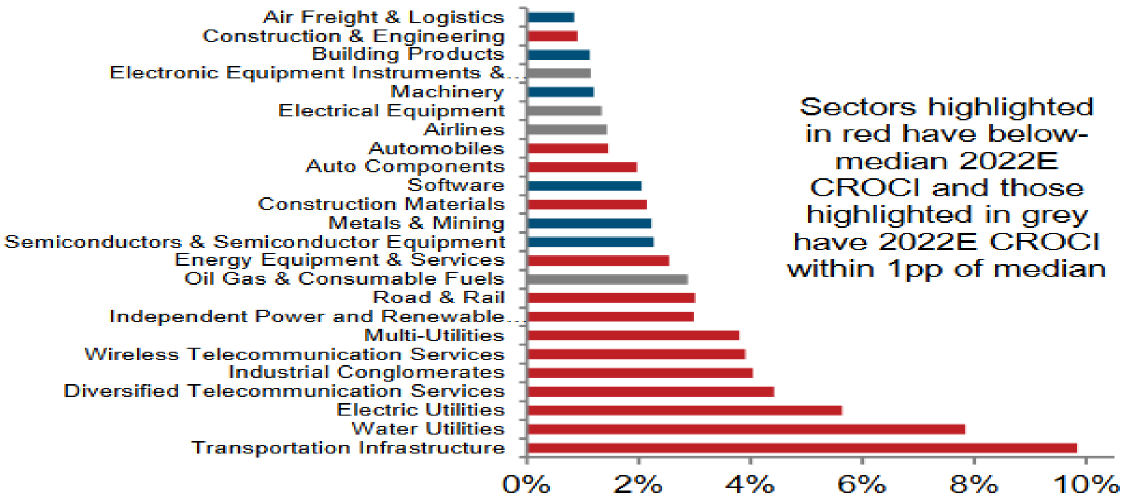
Investment needs are particularly urgent in "Greenablers": sectors like semiconductors, copper/aluminum, electricity transmission, and cybersecurity that are critical building blocks for the green transition given their vital roles in energy efficiency, automation and electrification, and long project lead times (2-12 years).

Corporates aren't currently on track to meet these needs, though. Assuming longer-term Capex growth of 2.5% annually and an increased weighting of Green Capex of ~1.5% per year, annual incremental Green Capex this decade would average ~$0.4tn from publicly traded companies.

Over the last decade, the share of operating cash flow that public companies have reinvested into Capex and R&D has fallen from 60-70% to 50% in 2022E. Such lower reinvestment rates have in part resulted in greater free cash flow and stronger balance sheets, creating $1tn in annual spare capacity that can be directed to Green investment.

But many of the sectors critical to achieving Green Capex goals have below-average corporate returns, which may make management and investors more cautious about supporting an increase in Green Capex. To achieve higher returns, companies may need innovation, policy support, or to raise prices—we estimate that a 100bp increase in corporate returns would require a company to increase prices for their goods or services 1-4%

Sectors with below-average returns may need to raise prices
Revenue increase required for a 1% increase in corporate returns



Source: Goldman Sachs GIR.

It is important to notice how businesses are steadily becoming more active in aiming to be a driving force toward a carbon-neutral future, by adopting science-based emission reductions targets and increasing reliance on wind, solar, and other renewable energy sources

An important example known as the We Mean Business Coalition is advocating businesses to adopt sustainable practices in kind. From Ikea to Sony to Coca-Cola, the coalition has organized more than 7000 businesses to commit to sustainability on top of whatever regulations are enacted by governments worldwide.

Far from being a purely altruistic cause, these businesses have joined the fight against global warming because recent studies have revealed that sustainability aligns the world’s long-term future with their own self-interest. After Morgan Stanley’s Institute for Sustainable Investing analyzed the performance of over 10,000 open-end mutual funds and 2,000 Separately Managed Accounts (SMAs) over seven years, the firm “ultimately found that investing in sustainability has usually met, and often exceeded, the performance of comparable traditional investments. This is on both an absolute and a risk-adjusted basis, across asset classes and over time.

These sustainable investment approaches are only going to grow in number and size in the coming years, according to Chris Geczy, adjunct finance professor and academic director of the Wharton Wealth Management Initiative. What that suggests is that investors worldwide are beginning to buy into the emerging research—that you don’t sacrifice return potential by integrating ESG. Put another way, the research shows that you can do good for the planet’s future while also doing well for yourself.

“It’s not a question of whether to adopt” a sustainable investment strategy, Geczy said, “but how to adopt and how much.”

And those who act decisively and early, with a deliberate analysis of their investments’ exposure to climate risk, are likely to see the greatest benefit from changes in patterns of investment in sectors most exposed to climate change.

5. EMPIRICAL ANALYSIS

The goal of our analysis is to investigate whether we could find empirical shreds of evidence of a relationship between market volatility and uncertainty regarding policies in general, with a particular focus on climate-related policies.

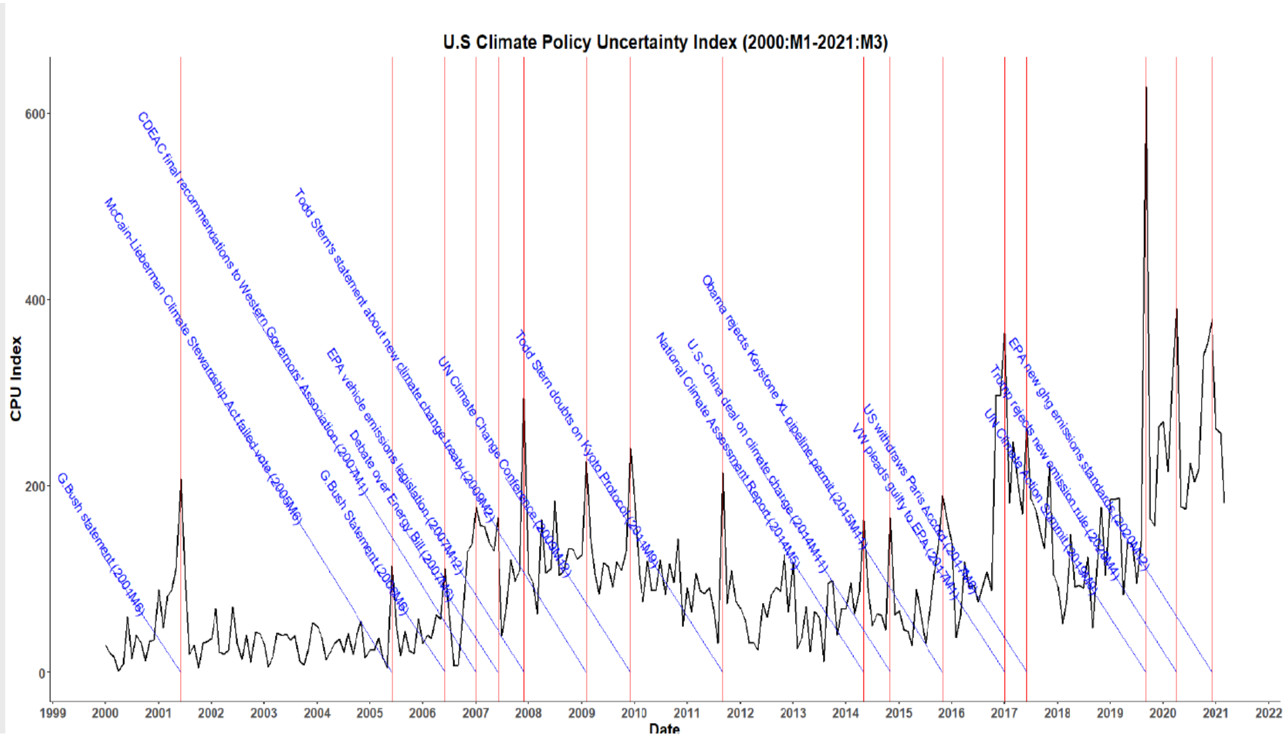
We will use statistical tools to perform a multi-level analysis of the relationship between our market volatility indicator (VIX) and different indices.

5.1 DATA

To perform this empirical analysis, we used data from www.policyuncertainty.com, a website that makes available a numerous variety of indices. In particular, we used data from January 1990 to September 2022 from the following Indexes:

- U.S. Climate Policy Uncertainty Index: developed by Konstantinos Gavriilidis in "Measuring Climate Policy Uncertainty". Gavriilidis follows the methodology in "Measuring Economic Policy Uncertainty" by Scott R. Baker, Nicholas Bloom and Steven J. Davis. He searches for articles in eight leading US newspapers containing the terms {"uncertainty" or "uncertain"} and {"carbon dioxide" or "climate" or "climate risk" or "greenhouse gas emissions" or "greenhouse" or "CO2" or "emissions" or "global warming" or "climate change" or "green energy" or "renewable energy" or "environmental"} and ("regulation" or "legislation" or "White House" or "Congress" or "EPA" or "law" or "policy"} (including variants such as "uncertainties", "regulatory", "policies", etc.).

He scales the number of relevant articles per month with the total number of articles during the same month. Next, these eight series are standardized to have a unit standard deviation and then averaged across newspapers by month.



- U.S Daily News Index: The daily news-based Economic Policy Uncertainty Index is based on newspaper archives from Access World New's NewsBank service. The primary measure for this index is the number of articles that contain at least one term from each of the 3 sets of terms. The first set is economic or economy. The second is uncertain or uncertainty. The third set is legislation or deficit or regulation or congress or federal reserve or white house.

- VIX Index: The VIX Index is a calculation designed to produce a measure of constant, 30-day expected volatility of the U.S. stock market, derived from real-time, mid-quote prices of S&P 500® Index (SPX℠) call and put options. On a global basis, it is one of the most recognized measures of volatility, widely reported by financial media and closely followed by a variety of market participants as a daily market indicator.

5.2 METHODOLOGY

In order to understand whether we could explain part of the volatility of the stock market with its empirical relationship with policy uncertainty, we used two different statistical models:

- ARIMAX: Autoregressive integrated moving average models extend ARIMA models through the inclusion of exogenous variables X. We write an ARIMAX(p,d,q) model for some time series data y_t and exogenous data X_t , where p is the number of autoregressive lags, d is the degree of differencing and q is the number of moving average lags

as:

$$\Delta^D y_t = \sum_{i=1}^{p} \phi_i \Delta^D y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \sum_{m=1}^{M} \beta_m Xm,t + \epsilon_t$$

- GARCH – X: In the GARCH-X model the effect of extraneous factors on the conditional variance is taken into consideration. This refinement of GARCH models becomes more dominant in various practical scenarios, especially in the event of unaccounted information from other factors can affect GARCH estimations

Mean model:

$$\varphi(B)(1-B)^d Y_t = \theta(B)\varepsilon_t + \sum_{s=0}^{l} \sum_{k=1}^{r} \gamma_{ks} X_{k,t-s}$$

Variance model:

$$\sigma^2{}_t = a_0 + \sum_{i=1}^{p} a_i \in^2{}_{t-i} + \sum_{j=1}^{q} b_j \sigma^2{}_{t-j} + \sum_{s=1}^{l} \sum_{k=1}^{r} \gamma_{ks} X_{k,t-s}$$

5.3 RESULTS

- VIX and U.S. DAILY NEWS INDEX

Using the daily data from January 1990 to September 2022 of both the VIX index and the U.S Daily News Index, we proceeded to perform a simple regression analysis to understand whether we could notice some correlations between the two indexes.

OLS Regression Results

Dep. Variable:	Vix value	R-squared:	0.161
Model:	OLS	Adj. R-squared:	0.161

	coef	std err	t	P>|t|	[0.025	0.975]	
const	15.2593	0.136	111.97	0.000	14.992	15.526	***
daily_policy_index	0.0417	0.001	39.748	0.000	0.040	0.044	***

We observe that there is an important linear relationship between the values of VIX and the U.S. Daily News Index, the latter being able to explain approx. 16% of the variability in mean of the VIX Index through its linear relationship.

In order to find more complex and sophisticated relationships, we constructed an ARIMA model on the dependent variable (the VIX Index) in an attempt to clean the information we have from the VIX index from its typical autoregressive and nonstationary behavior.

We took the log return of the VIX Index and, confronting different ARIMA through the Akaike information criterion (AIC) we decided to implement an ARIMA(1,4,1).

Then, looking for a relationship between the VIX Index and the U.S. Daily News Index, we constructed an ARIMAX, able to explain both the autoregressive and non-stationary components of the VIX index and its relationship with an exogenous component, in this case: the U.S. Daily News Index.

SARIMAX Results

Dep. Variable:	value	No. Observations:	8246
Model:	SARIMAX(1, 4, 1)	Log Likelihood	818.667
AIC	-1627.333		

	coef	std err	z	P>|z|	[0.025	0.975]	
const	-1.005e-10	1.47e-12	-68.319	0.000	-1.03e-10	-9.77e-11	***
daily_policy_index	-6.03e-05	1.65e-05	-3.648	0.000	-9.27e-05	-2.79e-05	***
ar.L1	-0.9245	0.005	-202.012	0.000	-0.934	-0.916	***
ma.L1	-0.9738	0.014	-67.697	0.000	-1.002	-0.946	***
sigma2	0.0481	0.001	56.748	0.000	0.046	0.050	***

From the results, we noticed that even when taking in account its autoregressive and non-stationary behavior, the VIX Index still presents an important relationship with the U.S. Daily News Index.

We could interpret this finding as empirical proof of an underlying dependence between the volatility expected in the stock market and the amount of news coming out about policy uncertainty.

In an attempt to investigate the matter further, we tried to construct a GARCH-X model, following the same reasoning before to investigate the volatility of the log-differences of the VIX index in relationship with its best-fitting autoregressive model, the autocorrelations of its error term and an exogenous variable, the U.S. Daily News Index.

Model: GARCH(1,1) [Bollerslev] (Normal)*

Dependent variable: ld_VIX_value

Sample: 1990-01-04 -- 2022-09-30 (T = 8244), VCV method: Hessian

Conditional mean equation

	coefficiente	errore std.	z	p-value	
const	0,001586	0,00112	1,413	0,1576	
daily_policy_index	-1,7878e-05	9,412e-06	-1,899	0,0575	*
AR1	-0,0776923	0,01246	-6,232	4,61e-010	***

Conditional variance equation

	coefficiente	errore std.	z	p-value	
const	0,000427	5,783e-05	7,389	1,48e-013	***
daily_policy_index	1,065e-06	3,217e-07	3,313	0,0009	***
alpha	0,1327	0,0116	11,40	4,31e-030	***
beta	0,7504	0,0223	33,55	8,56e-247	***

These encouraging results strengthen our hypothesis: being able to explain part of the stock market's volatility through an indicator of policy uncertainty.

We can see that in both the conditional mean and the conditional variance equations our exogenous variable, the U.S. Daily News Index, assumes significance.

Therefore, we can conclude that both the mean value and the variance of the VIX Index can be partly explained by its relationship with the U.S Daily News Index.

- VIX AND CPU

As done previously, we start by looking at the linear relationship between the VIX Index and the Climate Policy Uncertainty Index.

OLS Regression Results

Dep. Variable:	value	R-squared:	0.016
Model:	OLS	Adj. R-squared:	0.014

	coef	std err	t	P>|t|	[0.025	0.975]	
const	17.8504	0.792	22.552	0.000	16.294	19.407	***
cpu_index	0.0172	0.007	2.546	0.011	0.004	0.030	**

From these results, we are positive about the presence of a linear relationship between the two indices, even though as we can see from the R-Squared, it does little to nothing in explaining the variability of the dependent variable, in this case: the VIX Index.

Following the same reasoning as our previous analysis, we take a look at an ARIMAX model that has (1,4,1) as ARIMA's values but in this case, we will put the Climate Uncertainty Policy Index as an added exogenous variable.

SARIMAX Results

Dep. Variable:	value	No. Observations:	392				
Model:	SARIMAX(1, 4, 1)	AIC	575.568				

	coef	std err	z	P>|z|	[0.025	0.975]	
const	-3.066e-07	3.42e-09	-89.597	0.000	-3.13e-07	-3e-07	***
cpu_index	0.0002	0.000	0.583	0.560	-0.000	0.001	
ar.L1	-0.7052	0.029	-24.385	0.000	-0.762	-0.649	***
ma.L1	-0.9989	0.341	-2.932	0.003	-1.667	-0.331	***
sigma2	0.2426	0.083	2.936	0.003	0.081	0.405	***

Without surprise, we found out that we were not able to reject the null hypothesis of no significance for the coefficient of the Climate Policy Uncertainty Index. Therefore, we notice that once the variability of the log difference of the VIX's monthly mean value has been explained by its autoregressive and non-stationary behavior, its relationship with the Climate Uncertainty Police Index is of no use in explaining the volatility in the stock market trough a policy uncertainty related index.

We then implement a GARCH-X model to understand whether, at least, we can notice some shreds of relationship when looking at the conditional variance model of the VIX Index that has the Climate Policy Uncertainty Index as an exogenous regressor.

Model: GARCH(1,1) [Bollerslev] (Normal)*

Dependent variable: ld_value

Sample: 1990:03 -- 2022:08 (T = 390), VCV method: Hessian

Conditional mean equation

	coefficiente	errore std.	z	p-value
const	-0,0185	0,01697	-1,090	0,2755
cpu_index	0,00016	0,00018	0,8746	0,3818
AR1	-0,0006	0,0552	-0,01088	0,9913

Conditional variance equation

	coefficiente	errore std.	z	p-value	
const	0,0055	0,0061	0,8972	0,3696	
cpu_index	0,00025	4,246e-05	5,815	6,05e-09	***
alpha	0,0381	0,0548	0,6944	0,4875	
beta	-0,236	0,1727	-1,366	0,1719	

As expected, we notice that in the conditional mean equation of the VIX Index GARCH-X model, there is no relationship between the two indexes. This does not come unexpected since we already saw in the ARIMAX model that there is no relationship in mean between the log-difference of the VIX Index and the Climate Policy Uncertainty Index values.

It does show, though, a significant relationship in the conditional variance equation of the VIX Index GARCH-X model, meaning that the volatility of the VIX Index is not independent of the Climate Policy Uncertainty Index's values.

We can comment that part of the VIX variance can be explained by its relationship with the Climate Policy Uncertainty Index.

5.4 NOTES

For the sake of truth and science, this matter needs to be investigated further. It is an approximate work intended as a learning experience. It does shows some interesting results in terms of relationship between the amount of policy uncertainty and market volatility but it definetely presents some flaws.

The second investigated relationship presents a major flaw that compromises most of the work. Unfortunately, The Climate Policy Uncertainty Index presents data only on monthly basis, which forced us to use the monthly mean of the VIX Index. We are fully aware that by doing that we cut most of the information out and it is an exaggerated approximation.

In general, some models present some flaws that could have been solved if worked differently and by going deeper into the math behind them but unfortunately deadlines and a lack of experience played a crucial role.

We still think that our results could be useful in trying to figure out how much important the uncertainty coming from policy-related issues is in understanding what causes volatility in the stock market and therefore, how much the investors are impacted by the policy-related uncertainty.

6. REFERENCES

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7. CODE

7.1 PYTHON

```
"""

import pandas as pd

import numpy as np

from sklearn.linear_model import LinearRegression

import statsmodels.api as sm

from statsmodels.graphics.tsaplots import plot_pacf

from statsmodels.graphics.tsaplots import plot_acf

import matplotlib.pyplot as plt

from itertools import product

from tqdm import tqdm_notebook

from statsmodels.tsa.statespace.sarimax import SARIMAX

from arch.univariate import ARX, GARCH, ZeroMean, arch_model

#create a dataset with the value per month of the Climate policy uncertainty Index

data_cpu=pd.read_csv(r'C:\Users\User\Desktop\Greening Energy Market and Finance\CLIMATE-RELATED RISK AND COMMODITY MARKET (I.C.)\Assignment - Group work\CPU_csv.csv',index_col=('date'))

print (data_cpu)

#create a dataset with the daily values of the VIX Index

data_vix=pd.read_csv(r'C:\Users\User\Desktop\Greening Energy Market and Finance\CLIMATE-RELATED RISK AND COMMODITY MARKET (I.C.)\Assignment - Group work\vixvalue.csv',index_col=('date'))

print (data_vix)

data_news=pd.read_csv(r'C:\Users\User\Desktop\Greening Energy Market and Finance\CLIMATE-RELATED RISK AND COMMODITY MARKET (I.C.)\Assignment - Group work\data_news.csv')

print (data_news)

#create a dataset with the monthly average value of the VIX Index

data_vix.index = pd.to_datetime(data_vix.index)

data_vix_monthly = data_vix.resample('M').mean()

#select datas within the timeframe available for both indexes

data_vix_monthly.drop(data_vix_monthly.tail(4).index,inplace = True)

data_cpu.drop(data_cpu.head(33).index,inplace=True)

data_news.drop(data_news.head(1827).index,inplace = True)
```

```
data_news.drop(data_news.tail(6).index,inplace = True)
data_news_daily = data_news.iloc[:,3]
data_news_daily.index= pd.date_range(start = '01-02-1990', end= '09-30-2022')
data_news_daily= data_news_daily[data_news_daily.index.isin(data_vix.index)]
data_vix.drop(data_vix.tail(21).index,inplace = True)

######### Linear regression CPU-VIX
x_cpu = sm.add_constant(data_cpu)
x_cpu = x_cpu.reset_index(drop = True)
data_cpu_noindex= data_cpu.reset_index(drop = True)
y_monthly = data_vix_monthly.reset_index(drop = True)
model2=sm.OLS(y_monthly,x_cpu)
results= model2.fit()
print(results.summary())
########## SARIMAX test with extrogenous variable CPU-VIX
# fit model
y_monthly_log = np.log(y_monthly)
y_monthly_log_diff = y_monthly_log.diff()
data = y_monthly_log_diff.drop(y_monthly_log_diff.index[0])
# check the pacf and acf plots
plt.figure(figsize=[15, 7.5]); # Set dimensions for figure
plt.plot(y_monthly_log_diff)
plt.title("Log Difference of VIX Index")
plt.show()
plot_pacf(y_monthly_log)
plot_acf(y_monthly_log)
#function to try and find the best parameters for the SARIMA model
def optimize_SARIMA(parameters_list, d, D, s, exog):
    """
        Return dataframe with parameters, corresponding AIC and SSE
        parameters_list - list with (p, q, P, Q) tuples
        d - integration order
        D - seasonal integration order
        s - length of season
        exog - the exogenous variable
    """
```

```
    results = []
    for param in tqdm_notebook(parameters_list):
        try:
            model = SARIMAX(exog, order=(param[0], d, param[1]), seasonal_order=(param[2], D, param[3], s)).fit(disp=-1)
        except:
            continue
        aic = model.aic
        results.append([param, aic])

    result_df = pd.DataFrame(results)
    result_df.columns = ['(p,q)x(P,Q)', 'AIC']
    #Sort in ascending order, lower AIC is better
    result_df = result_df.sort_values(by='AIC', ascending=True).reset_index(drop=True)
    return result_df
p = range(0, 4, 1)
d = 2
q = range(0, 4, 1)
P = range(0, 4, 1)
D = 0
Q = range(0, 4, 1)
s = 0
parameters = product(p, q, P, Q)
parameters_list = list(parameters)
print(len(parameters_list))
optimize_SARIMA(parameters_list,1,4,1,y_monthly_log_diff)
# we find that the best ARIMA value based on AIC is ARIMA(1,4,1)
model = SARIMAX(y_monthly_log_diff, exog=x_cpu, order=(1, 4, 1), seasonal_order=(0, 0, 0, 0))
model_fit = model.fit(disp=False)
print(model_fit.summary())
data_news=pd.read_csv(r'C:\Users\User\Desktop\Greening Energy Market and Finance\CLIMATE-RELATED RISK AND COMMODITY MARKET (I.C.)\Assignment - Group work\data_news.csv')
print (data_news)
######### Linear regression Daily-VIX
x_Daily= sm.add_constant(data_news_daily)
x_Daily = x.reset_index(drop = True)
data_news_noindex= data_news_daily.reset_index(drop = True)
```

```
y_daily = data_vix.reset_index(drop = True)
y_daily_log = np.log(y)
y_daily_log_diff = y_daily_log.diff()
data = y_log_diff.drop(y_log_diff.index[0])
model2=sm.OLS(y,x)
results= model2.fit()
print(results.summary())
p = range(0, 4, 1)
d = 2
q = range(0, 4, 1)
P = range(0, 4, 1)
D = 0
Q = range(0, 4, 1)
s = 0
parameters = product(p, q, P, Q)
parameters_list = list(parameters)
print(len(parameters_list))
optimize_SARIMA(parameters_list,1,1,2,y)
model = SARIMAX(y_daily_log_diff, exog=x_Daily, order=(1, 4, 1), seasonal_order=(0, 0, 0, 0))
model_fit = model.fit(disp=False)
print(model_fit.summary())
# GARCH MODELS
#GARCH model bt\w VIX and CPU
mod = arch_model(data_vix_monthly,x=data_cpu , mean="ARX", lags=1, power=2)
res = mod.fit(disp="off")
print(res.summary())
#Garch model bt\w VIX and Daily News Index
mod_2 = arch_model(data_vix,x=data_news_daily , mean="ARX", lags=1, power=2)
res_2 = mod_2.fit(disp="off")
print(res_2.summary())
```