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List of Abbreviation

Akaike Information Criterion: AIC

Climate Policy Uncertainty: CPU

Durbin-Watson statistic: DW

Geopolitical Risk: GPR

Global Financial Cycle: GFCy[1]

Global Financial Uncertainty: GFU

Greenhouse Gas: GHG

Intergovernmental Panel on Climate Change: IPCC

Mean Absolute Error: MAE

Mean Absolute Percent Error: MAPE

National Aeronautics and Space Administration: NASA

National Oceanic and Atmospheric Administration: NOAA

Ordinary Least Squares: OLS

Research and Development: R&D

Root Mean Squared Error: RMSE

Variance Inflation Factor: VIF

Wall Street Journal Climate Change News Index: WSJ

World Meteorological Organization: WMO

[1] GFCy is used in this context to refer to the Global Financial Cycle, distinguishing it from the term GFC, which commonly refers to the Global Financial Crisis.

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Abstract

In this study we investigate the relationship among climate related risks and global financial cycle (GFCy). We provide strong empirical evidence in favor to the predictive power of climate related risks. We analyze data of both physical and transition risks, which form the climate risk. We construct a predictive model based on the climate quants. The findings reveal a strong connection between the GFCy and both physical and transition risks. More specifically, water & drought, extreme temperatures and Wall Street Journal (WSJ) index have a negative impact on GFCy, with the strongest connection to be with WSJ Index each affect negatively the GFCy in a different period lag. The opposite occurs to happen for the transition risk as climate summits, carbon tax and Intergovernmental Panel on Climate Change (IPCC) reports have a positive effect on GFCy, similarly in a different period lag. The United States Climate Policy (USCP) has a negative, albeit low, impact on the GFCy. The in-sample forecast provides satisfactory results. Additionally, we performed a multi-step ahead forecast, revealing that the model performs better in the short term comparted to the long term.

Keywords: Climate; physical risk; transition risk; global financial cycle.

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1 | Introduction

Could it be argued that climate change is, at least in part, a direct result of the economic policies implemented by governments and organizations around the world? This assertion could be considered plausible if we carefully examine the extensive body of literature that analyzes the relationship between economic decision-making and environmental outcomes[2]. Climate change and its related risks may lead to a (negative impact regarding the economic growth, employment, stock markets, productivity, agricultural growth, etc. (Nordhaus, 2007; Nordhaus, 2017; Stevanovic *et al.*, 2017; Newman and Noy, 2023; Hong *et al.*, Yang *et al.*, 2023;).

In 1994 Nordhaus provided in his paper the figure of the circular flow of global warming science, impacts and policy (Nordhaus, 1994). Analyzing the linkages between the different sections of the economy, climate impacts, politics and economic dynamics, mentioning the last the two with a questing mark in order to make it clear that they do not yet exist. He also points out the implementation of policies, otherwise the question marks on the figure will fade away, leading us to live with more intensely consequences of the global warming.

Kjellstrom *et al.*, 2009 supported that the effects of climate change also have an impact on social well-being. It is undeniable that, of all sectors of work, the agricultural sector is affected to a significant extent, which, as mentioned above, leads to a decrease in agricultural production.

According to research by Wilson (2018), conducted across the entire industry, weather phenomena have significant impacts on local economic activity in the short term, significantly influencing employment growth, differing from region to region,

[2] Nowadays it is certain that climate change is a result of human activities, and its effects are seen more and more often as every year records of temperature rise are broken. The leading international body of the assessment of climate science, IPCC has informed the world in its reports that the emissions from human activities have been the dominant cause of observed global warming since the mid-20th century. IPCC's sixth assessment report (AR6) concluded that it is unequivocal that the burning of fossil fuels and deforestation have led to an increase in global temperatures, changing weather patterns and rising sea levels. IPCC is not the only scientific body supporting the conclusion that climate change is a result of the human-included activities. World Meteorological Organization (WMO), the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA) are some of the scientific bodies that support this view. WMO in its latest publication[2] states that 2023 was the warmest year ever recorded, the global average near-surface temperature was at 1.45° Celsius above the pre-industrial baseline.

with the most significant impacts observed in the construction, mining, timber, hospitality, etc. sectors.

In the last decade or so, there is a growing literature about the GFCy [3] (Rey, 2013)[4]. Rey argues that countries can maintain independent monetary policies by managing their capital accounts. Rey, also, claims that "global financial cycles are associated with surges and retrenchments in capital flows, booms and busts in asset prices and crises". The literature provides the US monetary policy and global risk aversion as the "drivers" of the GFCy. Needless to say, that the US dollar plays a significant role, decisions made by main central banks (as Federal Reserve Bank) about monetary policies affect the GFCy.

Nordhaus argued that economics appear as an endless field. Over the past five decades, great academics have constinstently highlifhted the potential consequences of climate change and its related risks to the economic stability. Climate change is not a temporary phenomenon, it is a permanent situation that is constantly becoming more and more dangerous for human health, the future of nature, and the economic development of countries. The appearance of climate change year by year becomes more intense through extreme natural phenomena that affect everyday life, such as very high temperatures on an annual basis, fires, rising water levels, floods, etc. Nowadays, it is more than clear that the climate risk is closely related to the economics both in macroeconomic and microeconomic level. Climate ralated risks create financial risks and economic consequences making this field even more attractive to study.

In this paper we will focus on the period of 2003M01 to 2017M06, due to the available data selected[5]. It is necessary to provide some of the most important events

[3] Mainly affected by the monetary policy of the US.

[4] For more read the recent paper of Miranda-Agrippino and Rey (2021).

[5] the timeline of the climate crisis during the full period of the research (2003M01 to 2017M06). The first important event was the awarding of the IPCC with the Nobel Peace Prize in February 2007. IPCC received the Nobel Peace Price together with Al Gore[5] for their contributions to increasing the awereness of climate change, laying the groundwork for climate action and linking climate change to peace and security. The Copenhagen Climate Summit[5] held in denmark in December 2009 was one of the important international efforts to combat climate change that took place during 2003 - 2017. The main goal of the conference was to establish a global framework for reducing the greenhouse gas emissions and to succeed the Kyoto Protocol. More specifically, the Copenhagen Climate Summit sought to the reduction of the emmissions for both developed and developing countries, establish financial mechanisms to help

that happened during the period of the study. We hypethetize a negative connection between the climate related risks and the GFCy. We used the climate data of the studies of Ardia *et al*. (2023) and Faccini *et al*. (2023), for the physical risk from the dataset we used the factors of global warming, extreme temperatures, natural disasters, water & drought, hurricanes & floods. For the transition risk we used from the same dataset the factors of international summits, United States Climate Policy, IPCC's reports, climate summits and carbon tax. In the end, not all the factors were used in the final mode as they were not statistically significant. The statistical significant variables of the dataset of Ardia *et al*. (2023) are the factors of water & drought, extreme temperatures and WSJ index (physical risk), IPCC's reports, carbon tax, climate summits, Unites States Climate Policy (transition risk). We also used the CPU of Gavriilidis's (2021), but we didn't concluded in the best fitting model because it was not statistically significant in any of the models that we created. Moreover, we used the data of Global Financial Uncertainty provided by Caggiano and Castelnuovo (2023), we concluded in the model the Global Financial Uncertainty (GFU), GFU country-specific factor and GFU regional factor all of three were related to GFCy. Additional, we used the data of Wall Street Journal (WSJ) Index of Engle *et al*. (2020) all of the models that we tested showed a close relationship between WSJ Index and GFCy. In order to interpret the GFCy we used data from Federal Reserve Bank of St. Louis and Yahoo Finance. More specifically, we used the data of the Market Yield on United States Treasury Securities at 10-Year Constant Maturity, quoted on an investment basis, the Global Economic Policy Uncertainty Index the Consumer Price Index, the Capital Flow equity, United States Gross Domestic Product, the United States Stock, United

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developing countries in adapting to climate change and adopting greener technologies and setting a legally binding agreement to limit global warming below 2ºC compared to pre-industrial levels. The second important conferences that took place was the Paris Agreement in December 2015. The Paris Agreements sought to limit the blobal warming below 2ºC at the level of the pre-industrial levels. Also, it pursue efforts to limit the temperature increase to 1.5 ºC which has been described by the scientists as the point which will significantly recude the risks of climate impacts. Also, the paris agreement sought to achieve net-zero greenhouse gas (GHG) emissions in the second half of the century. Moreover, Paris Agreement sought to financial support mainly to daveloping nations in order to adapt to climate change. 2016 was described as the hottest year ever recorded, some of the results of the 2016's Record Heat was the ecosystem stress where highet temperatures exacerbated doughts and water scarcity, wildlife faced habitat stress, economic losses due to damages particulary
from floods, huriccanes and wildfires.

States Bond Yields of and S&P 500 respectively.

Several models were developed for the analysis; however, we will present only three of them. The model that bests fits the data (model 1) will be discussed in the main analysis while the results of the other two models will be presented in the section of the appendix section.

The findings of this study present supporting evidence for our novel hypothesis. In particular, the factors of water & drought and extreme temperatures have a negative impact on the GFCy over a seven-period lag and four-period lag respectively. For the transition risk the analysis showed that climate summits and carbon tax and IPCC's reports have a positive effect on the GFCy in a three-period lag, one-period lag and twenty-period lag respectively.

The rest of the paper is structured as follows. Section 2 presents the literature review. In the 3rd section we present the data we used for the study. Section 4 provides the methodology we followed. The theoretical framework is presented in section 5. The paper concludes in section 6.

2 | Literature Review

There will always be uncertainty in understanding a system as complex as the world's climate. However, there is now strong evidence that significant global warming is occurring. The evidence comes from direct measurements of rising surface air temperatures and subsurface ocean temperatures and from phenomena such as increases in average global sea levels, retreating glaciers, and changes to many physical and biological systems. It is likely that most of the warming in recent decades can be attributed to human activities (IPCC 2001)"[6]. Since then, numerous of scientific evidence continue to claim that human activities are responsible for the climate change and its related risks[7] (see, e.g., M. Lynas *et al*., 2021; F. Myers *et al*., 2021; J. Cook *et al*., 2016; Doran & Zimmerman, 2009).

High temperatures tend to reduce economic growth in countries with low living standards. They are also likely to reduce the rate of production and hence growth. This effect is primarily observed in agricultural and industrial markets (see also Nordhaus *et al*., 1994; Moore *et al*., 2014; Schlenker *et al*., 2006), but they equally affect the political stability of the country (Dell *et al*., 2012). The increase in the average temperature in the United States in the summer has a largely negative effect on the growth of gross state product, with the opposite being observed during autumn, more specifically, the increase in temperature in the autumn months has a positive effect on gross state product (Colacito *et al*., 2019). The study by Pycroft *et al*. (2015) suggests that the rise of the sea-level effects the global economy. They 25 world regions by using a general

[6] see also Statement on climate change from 18 scientific associations (2009), IPCC Fifth Assessment Report, Summary for Policymakers, SPM 1.1 (2014), IPCC Fifth Assessment Report, Summary for Policymakers, SPM 1 (2014), AAAS Board Statement on Climate Change (2014), GSA Position Statement on Climate Change (2015), ACS Public Policy Statement: Climate Change (2016-2019), Climate at the National Academies, Fourth National Climate Assessment: Volume II (2018), Society Must Address the Growing Climate Crisis Now (2019), Global Climate Change and Human Health (2019), Climate Change: An Information Statement of the American Meteorological Society (2019), American Physical Society (2021), IPCC Sixth Assessment Report, Working Group 1 (2021), IPCC Sixth Assessment Report, Working Group 2 (2022), IPCC Sixth Assessment Report, Working Group 3 (2022).

[7] According to EPA there are two categories related to climate risk. The first category is transition risks includes risks that are Risks related to the transition to a lower-carbon economy. The second category is physical risks, this category includes Risks related to the physical impacts of climate change.

equilibrium model and conclude that in 2080 the sea level will rise to 1,75m which will lead to 0,5% of reduction of global GDP. More specific, their study supports that there is a positive impact of the temperature shocks on the poorest countries, with the richest countries being negatively affected. Evidence shows that, in South Africa, global warming and drought have a negative impact mainly on the tertiary sector and informal employment. The effects of drought are mainly observed in the tourism and transport industries (Gray *et al*, 2022).

Moreover, Berg *et al*. (2024) studied the performance of real GDP per capita growth regarding the temperature changes among 137 countries which provide, at least, data for the last 30 consecutive years. Their research suggests that there is a substantial heterogeneity of the performance of real GDP per capita growth because of the temperature changes among the countries.

World's GDP decreases by 12% when the global temperature increases by 1°C. Each ton of carbon dioxide provides a social cost equal to $1,056, also a 31% welfare loss bases on a moderated warming scenario. Large countries like the United States benefit in the terms of cost by decarbonization policy (Bilal and Känzig, 2024). The stock returns of the industry that provides help to businesses to decarbonize are positive corelated with the carbon prices, which ceases when there's carbon price uncertainty (Fuchs *et al*., 2024).

Engle *et al*. (2020) developed the Wall Street Journal (WSJ) Climate Change News Index and CH Negative Climate Change News Index to measure media coverage of climate change. The study shows that the higher Environmental Scores a stock firm provide a higher return on periods when negative is displayed. Building on this, Ye (2022) explore the impact of climate news risk on uncertainties in the energy market, economic policy, and financial markets.. His research showed that there is a positive correlation between the economic policy uncertainty and climate news risk, while noting a negative effect on energy market uncertainty. Moreover, climate news risk, since 2013, has a positive effect on the financial market uncertainty. Finally, it's worth noting that his research showed that during Climate Change Conferences (Copenhagen, Doha and Paris) acts as a positive factor - having better effect - on economic policy and energy market uncertainty with the smallest effect being observed on financial market uncertainty.

Faccini *et al*. (2023) constructed a climate risk index to examine correlations with stock performance on different sectors. Their research suggests that climate risk does not reflect the prices in the stock market but there is a risk generated by government intervention which impacts the stock prices. Also, their study suggests that climate risk does not provide a financial risk.

Thang Ho (2022) using the climate change index show that high climate news beta[8] funds react better by 0,24% monthly on a risk-adjusted basis. Moreover, his study shows that a high climate news beta stocks perform better than low climate news beta stocks by 0,36% on monthly basis.

Gavriilidis (2021) provides an Index that measures the Climate Policy Uncertainty (CPU) by linked events to the climate policy. His study shows that when the index reaches 50 points there is an economics shock which leads to the reduction of the industrial production by 1,5%, raise of the unemployment by 0,4%, raise of the commodity prices by 2% and to a raise of the consumer prices by 0,4%. Since then, significant scientific research has been developed. Using the CPU Index Mengxi He and Yaojie Zhang (2022) studied the predictability of oil industry. The results of the paper show that the CPU index provides a strong connection as a predictor of the future stock returns of the oil industry and other carbon emission-related industries and becomes weaker to non-related industries. Moreover, their study shows that CPU can provide information about the future cash flows related to the oil industry and means that CPU is economically and statistically significant. Furthermore, their study shows that the performance of the CPU provides better results when there are economics expansions. In addition to, the good performance of the CPU can be explained by the oil fundamentals and the attention of the investors.

Xin Xu *et al*. (2023) measured the China's CPU with daily and monthly data from the Chinese news from January 2000 to March 2022 and compared with the US's CPU by using the Distribution lag nonlinear model. Their study indicates that the China's CPU has the same growth trend as the US'S CPU, but both CPU's affect differently the stock markets. Regarding the China's CPU, the return from the stock market gets lower as the CPU increases, further increasing volatility which will lead to decreases in the future. Moreover, it is possible to create a bigger dependence in volatilities regarding both stock markets in the current period. The US CPU provides decreases in the short term regarding the returns in the stock market but provides the opposite effect in the long term. Changes in the CPU lead to an increase in the

[8] Climate news beta measures how sensitive a stock is to climate risk.

correlation of the two stock market volatilities.

Lastly, the research that was done by Tedeschi *et al*., (2024) study the impact of CPU on the European financial markets. Their study indicates that CPU shock affect the financial stocks. They observed a positive effect of high climate risk which leads to an increase on the returns of clean energy stocks. Moreover, when there are CPU shocks there can be seen a substitutability relationship between brown and clean energies.

Ardia *et al*. (2023) constructed the daily Media Climate Change Concerns index resulting from the climate change news published on the US's newspapers and newswires. Their study suggests that an unexpected increase in climate change concerns increases the stock prices of the green firms leading to a decrease on the brown firms' prices as an effect of the climate risk. Moreover, an unexpected increase in the climate change concerns leads to an increase in the discount rate of brown firms it can also associated with a decrease in the discount rate of green firms.

Rey and Agrippino developed the GFCy in 2013. The GFCy provides information about the relationship of global financial markets and how the movements in global liquidity, capital flows, and central bank policies impact the decisions of economies across the world. The main argument of Rey is that the GFCy is primarily driven by fluctuations in global liquidity, which mainly are affected by the monetary policies of major economies and mainly by the U.S. Also, Rey and Agrappino suggest that large spilover effects on capital flows, asset prices and credit condition happen as a result of the centrality of U.S. dollar, these effects are mainly observed in emerging markets.

Cerutti and Claessens (2024) analyzed 76 economies (small country) using data from 2000 to 2021. The study is based on quantifying the importance of GFCy regarding the domestic credit, local assets and capital flows. Their study provided that respective series common factor and conventional US GFCy-drivers provide variation on the domestic credit (about 30 percent), on the stock market returns (about 40 percent), on the house prices (about 60 percent), on the interest rates and on the government's bond spreads (more than 75 percent).

Caggiano and Castelnuovo (2023) measured the global financial uncertainty (GFU) by modeling together global, regional and country specific factors. Using a VAR analysis that achieves set identification via a combination of narrative, sign, ratio, and correlation restrictions, they estimate the global output after the effects of GFU shocks. Their study suggests that the GFU during the Great Recession contributed to a significant contraction in world output, estimated at around 13%. Also, when the financial conditions get worse as an effect of the GFU shocks it leads to an increasingly world output contraction.

Salisu *et al.* (2022) used historical and recent GPR datasets and studied the predictability of geopolitical risk and global financial. Their study suggests that rises in geopolitical risk (GPR) provides a negative effect on investments regarding risky assets. Moreover, By using an empirical model which allowed them to test the hypothesis that there is a negative connection between high GPR and investment in risky assets, using the same approach as Westerlund and Naraya (2012, 2015). Their forecasting results show that the predictive model of GFCy which includes GPR data performs better than the benchmark model which ignores the in-sample and out-sample. However, by using the measure which was developed by Baumeister *et al*. (2020) they ended up to similar findings and this leads to the conclusion that the financial markets have a response even to GPR.

In this paper, we aim to contribute to the existing literature by investigating the relationship between climate risk and the GFCy, with a particular focus on whether climate risk demonstrates predictability in relation to the GFCy. To explore this connection, we will conduct an in-sample forecasting analysis, providing insights into the potential influence of climate-related factors on financial market dynamics.

3 | Data and Descriptive Statistics

3.1. | Description of Data and Indicators

For the purpose of this thesis we utilized the index constructed by Ardia *et al*. (2023) which measures the performance of green stocks versus the brown stocks of the United States market, which arise from the climate change concerns[9]. To examine the relation between GFCy and Climate related risks, in this thesis we utilize monthly data that cover the period 2003M01 to 2017M06, as this was the only period during which all the variables in the dataset were consistently available. Moreover, we used the data that where given by Engle *et al*. (2020), which reach by 2017M06, WSJ index various information about the United States stock prices, bond yields, market volatility unemployment and other economic indicators as GDP, the data were primarily obtained by the Wall Street Journal[10]. To investigate the impact of transition risk we, also, use the data of Carbon Tax and Climate Summits (Ardia *et al*. 2023). We similarly incorporated data of the IPCC in order to examine the impact of IPCC's reports to the GFCy (Ardia *et al*. 2023).

In this research we, additionally, utilized The Global Financial Uncertainty Index developed by Caggiano and Castelnuovo (2023) which quantifies the level of uncertainty in financial markets, worldwide and its impacts on the economic performance. Moreover, we included both *regional* and *country-specific* factors data[11]. Additionally, we included the four climate change risk factors, natural disasters, global warming, international summits and U.S. climate policy, that are provided by Faccini *et al*.[12] (2023). For the GFCy, we used the data that from the work of Miranda-Agrippino and Rey (2021). The latest update of their work provides data from 1980M01 to 2019M04. In order to better interpret the GFCy we used the Global Economic Condition Indicator, Market Yield on United States Treasury Securities at 10-Year Constant Maturity, Consumer Price Index concerns All Urban Consumers, the Global Economic Policy Uncertainty Index, U.S. Capital Flow Equity, U.S. Volatility Index and the U.S. GDP, all data where obtained by the Federal Reserve Bank of St. Louis (FRED - ST. LOUIS FED, available at https://fred.stlouisfed.org), S&P500 data was

[9] Data are accessible at https://sentometrics-research.com/download/mccc/
[10] Available at pages.stern.nyu.edu/~jstroebe/Data/EGLKS_data.xlsx
[11] https://docs.google.com/spreadsheets/d/1dWZTTgTBMTvZQeWBFLxkiBS60C8A4TIg/edit?gid=2053097504#gid=2053097504
[12] Available at https://sites.google.com/site/econrenatofaccini/home/research

obtained by yahoo finance (available at https://finance.yahoo.com). We used the above economic data as control variables in order to approach as much the GFCy.

3.2. | Descriptive Statistics

TABLE 1 | Descriptive Statistics of the variables

	Mean	Median	Std. dev.	Skewness	Kurtosis
GECI	-0.04	0.03	0.44	-2.14	10.60
DGS10	3.23	3.31	1.05	0.05	1.65
ET	0.95	0.94	0.37	0.60	3.70
CPI	217.11	217.55	18.42	0.35	1.89
W&D	0.78	0.70	0.34	0.93	3.81
S&P 500	1.149	1.327	412.10	0.66	2.34
GEPU	115.12	109.13	44.53	0.90	3.72
WSJ	0.01	0.01	0.00	2.27	12.30
USS	0.96	0.78	0.66	3.11	15.85
IPCC	0.75	0.70	0.32	0.90	3.87
USBY	0.09	0.08	0.05	1.93	8.75
CFE	3.280	3.281	7.569	-0.43	5.46
VIX	19.04	16.49	8.57	2.47	10.82
GFU	0.02	-0.07	0.62	2.14	9.89
GFUCSF	0.31	0.13	1.54	2.13	9.58
GFURF	0.27	0.15	0.75	2.15	10.24
CT	0.80	0.58	0.32	0.37	3.01
CS	0.58	0.48	0.41	2.44	11.27
USGDP	17.081	16.891	1.244	0.19	2.35
GFCy	0.65	0.52	1.01	-0.12	3.62
USCP	0.65	0.33	0.94	3.14	18.16

Note: DGS10 is reffered to Market Yield on United States Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis, Percent, Monthly, Not Seasonally Adjusted, GEPU reffers to the Global Economic Policy Uncertainty Index: Current Price Adjusted GDP, Index, Monthly, Not Seasonally Adjusted, Consumer Price Index concerns All Urban Consumers: All Items in United States City Average, Monthly, Seasonally Adjusted, IPCC refferes to Intergovernmental Panel on Climate Change. USGDP reffers to the United Stated Gross Domestic Product. ET, W&D, CT, CS and USCP refer to extreme temperatures, water & drought, carbon tax, climate summits and United Stated climate policy, respectively. WSJ, USS, USBY, GFUCSF, GFURF, GFCy refer to Wall Street Journal index, United States stock, United States, global financial uncertainty country specific factors, global financial uncertainty regional factors, global financial cycle, respectively.

TABLE 2 | Descriptive Statistics - First Differences

	Mean	Median	Std.dev.	Skewness	Kurtosis
GEPU	0.24	-10.40	254.99	0.72	78.60
CPI	0.35	0.43	0.68	-14.87	119.51
DGS10	-0.01	0.01	0.21	0.47	67.55
IPCC	0.003	0.01	0.30	0.21	38.99
S&P 500	88.88	147.90	509.35	-0.61	44.84
USGDP	289.91	349.05	880.21	0.35	3.86

***Note*:** DGS10 is reffered to Market Yield on United States Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis, Percent, Monthly, Not Seasonally Adjusted, GEPU reffers to the Global Economic Policy Uncertainty Index: Current Price Adjusted GDP, Index, Monthly, Not Seasonally Adjusted, Consumer Price Index concerns All Urban Consumers: All Items in United States City Average, Monthly, Seasonally Adjusted, IPCC refferes to Intergovernmental Panel on Climate Change. USGDP reffers to the United States Gross Domestic Product.

Table 1 and 2 provide information about the Mean, Median, Standard Deviation, Kurtosis and Skewness of each variable in full period both in original data and first differences. The results of table 1 show that Extreme Temperatures and Water/Drought provide high mean values (close to 1) which both can be consindered significants factors, also provide positive skewness. These events also provide o kurtosis close to 4 suggesting a peaked dustribution and meaning that there are havier tails in the distribution which can lead us to the conclusion that these events are propably more likely to be presents than in a normal distribution. The mean of WSJ index is quite low (0,0066) leading us to the conclusion that it might be less influentail factor or it has a different measured scale. The kurtosis of WSJ index is quite high and suggests that the distribution has heavy tails. IPCC has a mean value equal to 0,7509 indicating that it is an important factor with a kurtosis close to 4 meaning that it, also, has a peak distribution as the extreme events. The mean of Carbon Tax is equal to 0,8038 thus can be classified as an important factor. The kurtosis is almost 3 which means that is following a normal distribution without extreme outliers. Climate Summits's mean is close to 0,6 making it a less important factor. Climate Summits provide a very high kurotsis (11,2749) meaning that the distribution is peaked with many extreme values. Overall, we conlude that the extreme events of Extreme Temperatures and Water/Drought are frequent.

TABLE 3 | Descriptive Statistics - Important Variables 2003M01 - 2007M01

	Mean	Median	Std. dev.	Skewness	Kurtosis
ET	0.63	0.59	0.25	1.25	5.05
W&D	0.50	0.45	0.18	1.03	4.36
IPCC	0.47	0.44	0.17	0.70	3.52
CT	0.47	0.42	0.20	0.79	3.03
CS	0.38	0.33	0.20	1.37	4.68
USCP	0.31	0.11	0.49	3.02	14.35

***Note*:** DGS10 is reffered to Market Yield on United States Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis, Percent, Monthly, Not Seasonally Adjusted, GEPU reffers to the Global Economic Policy Uncertainty Index: Current Price Adjusted GDP, Index, Monthly, Not Seasonally Adjusted, Consumer Price Index concerns All Urban Consumers: All Items in United States City Average, Monthly, Seasonally Adjusted, IPCC refferes to Intergovernmental Panel on Climate Change. USGDP reffers to the United States Gross Domestic Product. ET, W&D, CT, CS and USCP refer to extreme temperatures, water & drought, carbon tax, climate summits and United Stated climate policy, respectively.

TABLE 4 | Descriptive Statistics - Important Variables 2007M02 - 2017M06

	Mean	Median	Std. dev.	Skewness	Kurtosis
ET	1.07	1.04	0.32	0.82	4.55
W&D	0.89	0.82	0.32	0.93	3.75
IPCC	0.85	0.80	0.30	0.98	3.85
CT	0.93	0.90	0.26	0.83	3.41
CS	0.66	0.54	0.43	2.28	9.76
USCP	0.77	0.42	1.03	0.28	15.37

***Note*:** DGS10 is reffered to Market Yield on United States Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis, Percent, Monthly, Not Seasonally Adjusted, GEPU reffers to the Global Economic Policy Uncertainty Index: Current Price Adjusted GDP, Index, Monthly, Not Seasonally Adjusted, Consumer Price Index concerns All Urban Consumers: All Items in United States City Average, Monthly, Seasonally Adjusted, IPCC refferes to Intergovernmental Panel on Climate Change. USGDP reffers to the United States Gross Domestic Product. ET, W&D, CT, CS and USCP refer to extreme temperatures, water & drought, carbon tax, climate summits and United Stated climate policy, respectively.

Table 3 and 4 provide the descriptive statistics only for the variables that are related to climate risks. We devided the data into two periods. The first period is from 2003M01 to 2007M01 and the second period is from 2007M02 to 2017M06. We chose to devided the data into these two periods because in February 2007 IPCC received the Nobel Peace Prize in order to inform the world about the impact of climate change.

For the Extreme Temperatures the Mean and the Median values increased from 0,633 and 0,600 to 1.076 and to 1.047 respectively, which can be interpreted as extreme temperatures became more prevalent or more impactful over time. An increase in the Standard Deviation can be observed, from 0,257 to 0,325, indicating more variability in extreme temperature. Exactly the same increases can be observed for Water and Drought, Mean Median and Standard Deviation increased from period one to the second period, from 0.507, 0.452 and 0.186 to 0.891, to 0.829 and to 0.324 respectively.

We can conclude that, also, water and drought provide a increase on the related events. Carbon Tax provide an increase (almost double) in the Mean from 0.474 to 0.933 and Median from 0.424 to 0.903 for period one to period two which can be interpreted as an increase of the Carbon Taxes. The Standard Deviation provides also a smaller increase from 0.203 to 0.265. Climate Summits also provide an double increase on the Mean and Median, more specifically, the Mean from 0.382 in the first period to 0.663 in the second period, the Median increased from 0.336 to 0.550, indicating an increase in the climate summits. The Standard Deviations provides an increase (more than double) from 0.206 to 0.436. The Mean ffor the United States Climate Policy increased more than double into the two periods from 0.315 to 0.777 also the Median increased from 0.115 to 0.424 suggesting that the United States provided a greater average activity but with variablity between high and low points. The Standard Deviation also increased from 0.492 to 1.034 which can reflect a large fluctuations in climate related policies over time.

4 | Methodology

In this section we formulate three empirical models to examine the impact of Climate related risks on GFCy. Literature provides numerus studies which focus on the correlation of climate risk and financial markets. In this chapter we construct three predictive models which connect climate related risks to GFCy. GFCy is shaped by the Capital in flow and outflow to risky assets. In this part we hypothesize that extreme climate physical risks, may affect the GFCy in a negative form and transition risk may affect GFCy in a positive form. A negative outcome is expected regarding the correlation of climate related risks and financial markets. To interpret climate related risks, for the transition risk we used data of the US's climate policy, IPCC's reports, climate summits and carbon tax, for the physical risks we used: extreme temperatures, water/drought and the WSJ index. For the financial conditions, we used data of S&P 500, Global Financial Uncertainty (both regional and country specific), US stock and US bond yields, Global Economic Condition Indicator, Market Yield on United States Treasury Securities at 10-Year Constant Maturity, Consumer Price Index concerns All Urban Consumers, the Global Economic Policy Uncertainty Index, U.S. Capital Flow Equity, U.S. Volatility Index and the U.S. Gross Domestic Product.

For the preparation of this paper, but also for the answer to the research question, a few models were examined, and the three best "fitted" models, and which fulfill the requirements of the OLS method. In this thesis. We will present and comment on the results of the best fitted model which is model 1. The results of the other two models will be presented in the appendix chapter.

4.1. Model Framework

4.1.1 Multiple Linear Regression Using Least Squares - Assumptions of Ordinary Least Squares

The analysis was done by using, for model 1 and model 2, the Ordinary Least Squares (OLS). Least squares specify a linear function with k explanatory variables in order to describe the behavior of independent variable (y):

The general model structure is:

$$\Delta(\mathrm{GFCy}_t) = \beta_0 + \sum_{i=1}^{n} \beta_i X_{it} + \varepsilon_t , \quad \epsilon_t \sim N(0, \sigma^2) \tag{1}$$

where β_i are the parameters estimated and $X_{i,t}$ are the explanatory variables.

To ensure that the estimates are unbiased and consistent OLS requires some assumptions called the Assumptions of the OLS:

1) ***Linearity:*** which refers to the relationship between the dependent variable and independent variables is linear.
2) ***No Perfect Multicollinearity:*** refers that the independent variables are not perfectly correlated.
3) ***Exogeneity of the Regressors:*** The error term ε is uncorrelated with the explanatory variables
4) ***Homoscedasticity:*** The variance of the errors is constant across all the observations.
5) ***No autocorrelation:*** refers that the errors are not correlated with each other.
6) ***Normality of the Errors:*** refers to the normally distribution of the errors ε.

The first two models were constructed with the OLS method while the third model was constructed with the combination of the OLS and autoregressive (AR) and moving average (MA).

4.2 The Predictive models

Based on (1) we formulated the models as follow:

<u>Model 1:</u>

$$\Delta(GFCy_t) = \beta_0 + \sum_{i=1}^{n} \beta_i X_{i,t} + \varepsilon_t$$

$$\begin{gathered} For\ X_{i,t} = \\ GECI_t, WD_{t-8}, WSJ_{t-1}, GFU_{t-2}, CFEQUITY_{t-2}, \Delta(DSG_{t-12}), \Delta(CPI_{t-4}), ET_{t-5}, \\ \Delta(\log(SNP_{t-7}), \Delta(GEPUCURRENT_{t-1}), USBY_{t-3}, \log(USS_{t-13}), \Delta(IPCC_{t-20}), \\ VIX_{t-1}, CT_{t-3}, CS_{t-3}, GFURF_{t-6}, GFUCSF_{t-2}, \Delta(GDP_t), USCP_{t-2} \end{gathered} \tag{2}$$

Model 2:

$$\Delta(GFCy_t) = \beta_0 + \sum_{i=1}^{n} \beta_i X_{i,t} + \varepsilon_t$$

$$\text{For } X_{i,t} = CPF_{t-3}, GECI_t, WD_{t-7}, WSJ_{t-1}, USEXR_{t-2}, GFU_{t-2}, CFEQUITY_{t-2}, \Delta(DSG_{t-12}), \Delta(CPI_{t-4}), ET_{t-4}, \Delta(\log(SNP_{t-7})), \Delta(GEPUCURRENT_{t-1}), USBY_{t-3}, \log(USS)_{t-11}, \Delta(IPCC_{t-20}), VIX_{t-1}, CT_{t-1}, CS_{t-1}, \Delta(GDP_t) \tag{3}$$

Model 3 ARMA (12,1):

$$\Delta(GFCy_t) = \beta_0 + \sum_{i=1}^{n} \beta_i X_{i,t} + \varepsilon_t$$

$$e_t = c_{12} e_{t-12} + d_1 \varepsilon_{t-1} + \varepsilon_t,$$

$$\varepsilon_t \sim N(0, \sigma^2)$$

$$\text{For } X_{i,t} = CPF_{t-3}, GECI_t, WD_{t-7}, WSJ_{t-1}, USEXR_{t-2}, GFU_{t-2}, CFEQUITY_{t-2}, \Delta(DSG_{t-12}), \Delta(CPI_{t-4}), ET_{t-4}, \Delta(\log(SNP_{t-7})), \Delta(GEPUCURRENT_{t-1}), USBY_{t-3}, \log(USS)_{t-11}, \Delta(IPCC_{t-20}), VIX_{t-1}, CT_{t-1}, CS_{t-1}, \Delta(GDP_t) \tag{4}$$

4.3 Best "Fitting" Model - Model 1

4.3.1. Stationarity of Variables

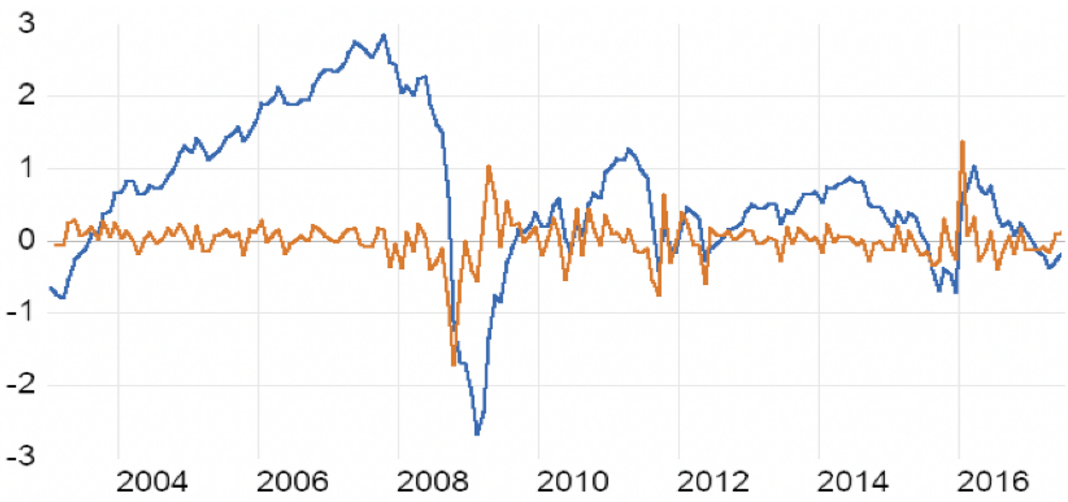
Among the three predictive models that are mentioned in the section 4.2, model 1 provided the best fit.

The first step of the analysis was to test each variable for stationarity, as stationarity is a key assumption for time series models. We did that by checking every variable for stationarity by using the Augmented Dickey-Fuller (ADF) test.

[Table 12 ABOUT HERE]

For each variable that was found non-stationary, we applied first differencing to achieve stationarity on the variables, as this method removes trends and stabilizes the mean of the series.

Figure 1 | First differences of Global Financial Cycle



Note: Figure 1 provides with the blue the graph of GFCy while the orange line provides the graph of the first difference of the GFCy.

4.3.2. Model performance

Step two involved assessing the statistical significance of the variables in the constructed model. We, also, checked the R-squared and the Akaike Information Criterion (AIC), to assess the model's fitting and predictive performance. This was done by "running" the equation of model 1 (2).

Table 3 Provides the results of the estimation of model 1. All the variables provide low probability (at 5% significance) concluding that all the variables are statistically significant in different period lags. R-squared is equal to 0,79 and AIC is equal to -0,81. The results lead to the conclusion that the model's R-squared value indicates the 79% of the variation in the dependent variable is explained by the independent variables that are included into the model. The AIC value of -0,81 suggest that the model is providing an efficient balance between a good fitting model and the model's complexity, in other word the model has a relatively low information loss when considering model complexity. Overall, the regression model performs well with explanatory power and significant variables. The results highlight the importance of both immediate and lagged effects.

Table 6, below, provides the results of the regression using the least squares method. The R-squared (0.790) explains the 79.0% of the variation in the dependent variable providing evidence of strong fit for the data. After accounting for the number of predictors, the model still explains a substantial 75.8% (adjusted R-squared) of the variation. The F-statistic (24.848, p = 0.0000) provides strong evidence that the model is highly statistically significant, indicating that the explanatory variables provide predictive power of GFCy. All the explanatory variables are statistically significant at 5%. The water & drought, extreme temperatures and the wall street journal index provide a negative coefficient -0.2087, 0.1379 and -18.1292 respectively on a different lag-period, showing that physical risk has a negative impact on the GFCy. Carbon tax, climate summits and IPCC's report provide a positive coefficient also on a different lagged-period, 0.1524, 0.1275 and 0.1416 respectively. With the exact opposite happening with the United States Climate Policy affecting the GFCy negatively by 0,0373.

Table 5 | OLS results

Dep. Var.: Δ(GFCy)
Method: Least Squares
Sample (adjusted): 2004M10 2017M06
Method: Least Squared

Variable	Coefficient	Std. Error	t-Statistic	Prob
C	-0.39	0.08	4.54	0.00
$GECI_t$	0.21	0.04	4.52	0.00
WD_{t-7}	-0.20	0.04	4.60	0.00
WSJ_{t-1}	-18.12	7.77	2.33	0.02
GFU_t	-0.32	0.03	8.53	0.00
CFE_{t-2}	-7.03E-06	1.88E-06	3.72	0.00
$\Delta(DGS10_{t-12})$	-0.19	0.06	3.04	0.00
$\Delta(CPI_{t-4})$	0.09	0.01	4.87	0.00
ET_{t-4}	-0.16	0.04	3.89	0.00
$\Delta(LOG(SNP_{t-7}))$	-0.91	0.34	2.63	0.00
$\Delta(GEPU_{t-1})$	-0.00	0.00	3.40	0.00
$USBY_{t-3}$	0.82	0.37	2.21	0.02
$LOG(USS_{t-11})$	-0.09	0.02	3.03	0.00
$\Delta(IPCC_{t-20})$	0.14	0.04	3.10	0.00
VIX_{t-1}	0.03	0.00	9.99	0.00
CT_{t-3}	0.15	0.05	2.82	0.00
CS_{t-1}	0.12	0.04	3.10	0.00
$GFURF_{t-6}$	0.11	0.02	4.29	0.00
$GFUCSF_{t-2}$	-0.10	0.02	4.90	0.00
$\Delta(GDP_t)$	0.00	0.00	2.28	0.02
$USCP_{t-2}$	-0.03	0.015	2.33	0.02

R-squared:	0.79	**Mean dep. Var:**	-0.007
Adj. R-squared:	0.75	**S.D. dep. Var:**	0.30
St. Error of Regr.:	0.15	**Akaike Info Crit.:**	-0.80
Sum of Sq. Res.:	3.03	**Schwarz Crit.:**	-0.39
Log-Likelihood:	82.91	**Hannan-Quinn Crit.:**	-0.64
F-statistic:	24.84	**Durbin-Watson Stat:**	2.44
Prob(F-statistic):	0.000		

4.3.3. Normality test

Next step was to check the model if is following a normal distribution. This was done by using the Jarque - Bera Test. which is calculated as:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}\,(k-3)^2\right), \tag{5}$$

where n is the number of the observations, S refers to the skewness, K is the kurtosis. S is calculated as:

$$S = \frac{\widehat{\mu_3}}{\widehat{\sigma_3}} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^3}{\frac{1}{n}\left(\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^{3/2}}, \tag{6}$$

K is calculated as:

$$K = \frac{\widehat{\mu_4}}{\widehat{\sigma_4}} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{\frac{1}{n}\left(\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^{2}}, \tag{7}$$

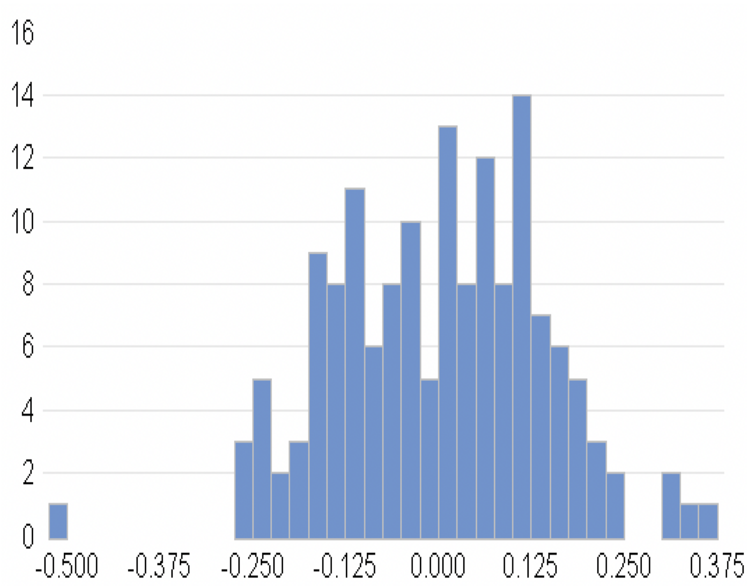
Where: $\widehat{\mu_3}$ and $\widehat{\mu_4}$ estimate the third and the fourth central moments, $\bar{x}$ is the mean, $\widehat{\sigma^2}$ refers to the variance.

The Jarque - Bera Hypotheses are:

- **Null hypothesis (H_0)**: The data is normally distributed.
- **Alternative hypothesis (H_1)**: The data is not normally distributed.

Table 6 provides the histogram and the results of the Jarque - Bera test of model 1. Jarque Bera = 1.74 with a probability equal to 0,42. We accept the null hypothesis which leads to the conclusion that the data are normally distributed.

Table 6 Jarque - Bera Test



Series: Residuals
Sample 2004M10 2017M06
Observations 153

Mean 9.81e-17
Median 0.015214
Maximum 0.372172
Minimum -0.521066
Std. Dev. 0.141195
Skewness -0.194176
Kurtosis 3.348726

Jarque-Bera 1.736719
Probability 0.419639

Note: Histogram and Jarque - Bera test

4.3.4. Autocorrelation Test

We checked for autocorrelation by examining the Durbin-Watson statistic (DW), which is equal to 2.45, and reviewing the correlogram. The DW statistic test the residuals from the regression for autocorrelation. The DW statistic is given by:

$$DW = \frac{\sum_{i=2}^{T}(e_t - e_{t-1})^2}{(\sum_{t=1}^{T} e_t^2)}, \quad (8)$$

where e_t refers to the residuals error at time t and T is the total number of the observations.

The DW statistic Hypothesis are:

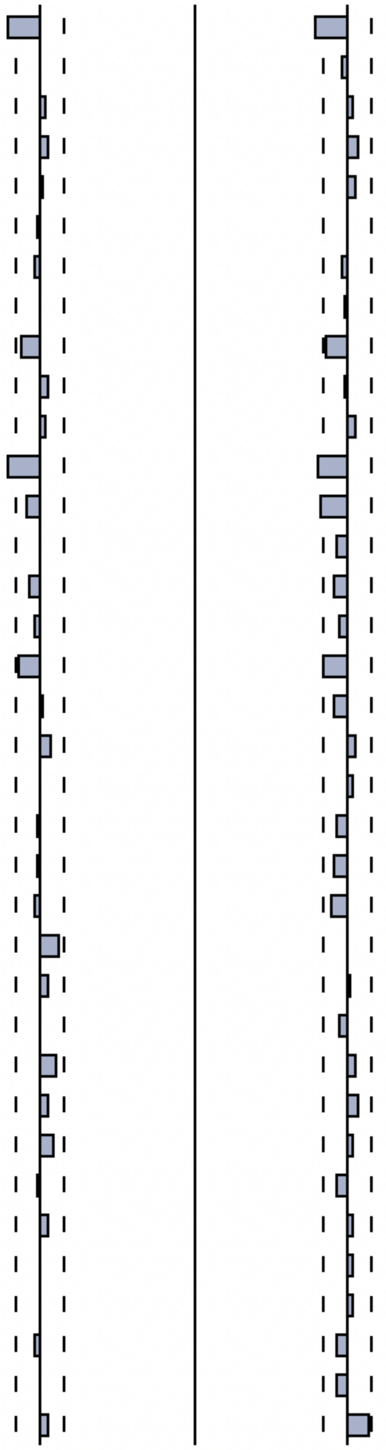
- **Null Hypothesis (H_0)**: No first-order autocorrelation ($DW \approx 2$).
- **Alternative Hypothesis (H_1)**: There is autocorrelation ($DW \neq 2$).

Since the DW statistic is equal to 2.45 we fail to reject the null hypothesis (H_0).

Table 7 | Q - Correlogram

Sample (adjusted): 2003M00 2017M06

Q-statistic probabilities adjusted for 20 dynamic regressors



Autocorrelation	Partian Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.225	-0.225	7.8783	0.005
		2	0.005	-0.048	7.8822	0.019
		3	0.038	0.030	8.1078	0.044
		4	0.049	0.068	8.4908	0.075
		5	0.020	0.052	8.5579	0.128
		6	-0.009	0.007	8.5721	0.199
		7	-0.032	-0.040	8.7410	0.272
		8	0.002	-0.024	8.7414	0.365
		9	-0.129	-0.148	11.488	0.244
		10	0.053	-0.009	11.958	0.288
		11	0.028	0.046	12.087	0.357
		12	-0.217	-0.196	20.029	0.067
		13	-0.087	-0.187	21.305	0.067
		14	0.000	-0.074	21.313	0.094
		15	-0.066	-0.091	22.063	0.106
		16	-0.031	-0.057	22.226	0.136
		17	-0.144	-0.169	25.832	0.078
		18	0.022	-0.085	25.917	0.102
		19	0.072	0.049	26.827	0.109
		20	-0.001	0.030	26.827	0.140
		21	-0.017	-0.073	26.877	0.175
		22	-0.017	-0.088	26.932	0.214
		23	-0.046	-0.111	27.317	0.243
		24	0.0129	0.005	30.353	0.140
		25	0.053	0.015	30.875	0.193
		26	-0.002	-0.051	30.876	0.233
		27	0.099	0.065	32.724	0.206
		28	0.044	0.072	33.094	0.232
		29	0.085	0.031	34.474	0.222
		30	-0.015	-0.073	34.515	0.261
		31	0.050	0.033	35.000	0.284
		32	0.005	0.031	35.004	0.327
		33	0.005	0.027	35.009	0.373
		34	-0.042	-0.076	35.358	0.404
		35	0.007	-0.077	35.366	0.404
		36	0.059	0.144	36.066	0.466

4.3.5. Heteroscedasticity Test

To check the model if provides heteroscedasticity we performed the Breusch-Pagan test, which provides information for non-constant variance in the residuals. Additionally, we examined the correlogram of the squared residuals to visually assess of any systematic patterns of autocorrelation in the variance of errors, which could indicate the presence of heteroscedasticity.

Table 8 | Breusch - Pagan Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Nyll hypothesis: Homoscedasticity

F-statistic	0.737		**Prob. F(20, 132)**	0.781
Obs*R-squared:	15.371		**Prob. Chi-Square(20)**	0.754
Scaled exp. SS	13.435		**Prob. Chi-Square(20)**	0.857

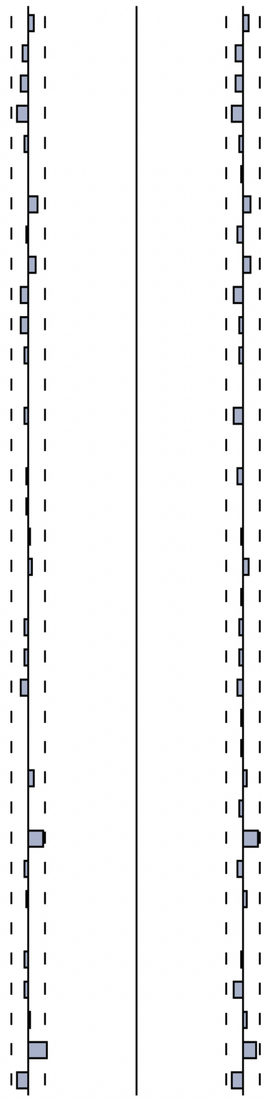
Variable	Coefficient	Std. Error	t-Statistic	Prob
C	0.007	0.017	0.439	0.660
$GECI_t$	-0.007	0.009	-0.770	0.442
WD_{t-7}	-0.008	0.009	-0.923	0.357
WSJ_{t-1}	-0.327	1.589	-0.205	0.838
GFU_t	-0.002	0.007	-0.294	0.768
CFE_{t-2}	-2.31E-07	3.85E-07	-0.600	0.549
$\Delta(DGS10_{t-12})$	-0.013	0.012	-1.030	0.304
$\Delta(CPI_{t-4})$	-0.004	0.003	-1.035	0.302
ET_{t-4}	0.012	0.014	0.849	0.748
$\Delta(LOG(SNP_{t-7}))$	0.014	0.007	2.022	0.045
$\Delta(GEPU_{t-1})$	-7.70E-06	0.0001	-0.076	0.933
$USBY_{t-3}$	-0.074	0.076	-0.971	0.333
$LOG(USS_{t-11})$	-0.004	0.006	-0.715	0.475
$\Delta(IPCC_{t-20})$	0.003	0.009	0.417	0.676
VIX_{t-1}	0.003	0.006	0.654	0.514
CT_{t-3}	0.003	0.004	0.756	0.450
CS_{t-1}	0.006	0.008	0.779	0.431
$GFURF_{t-6}$	0.012	0.005	2.223	0.027
$GFUCSF_{t-2}$	-0.002	0.004	-0.608	0.543
$\Delta(GDP_t)$	3.79E-05	3.18E-05	1.189	0.236
$USCP_{t-2}$	-0.002	0.003	-0.899	0.369

R-squared:	0.100	**Mean dependent var**	0.019
Adj. R-sq.:	-0.035	**S.D. dependent var**	0.030
St.Error of Reg.:	0.030	**Akaike Info Criterion:**	-3.983
Sum of Sq. Res.:	0.126	**Schwarz Criterion:**	-3.567

Log-Likelihood:	325.71	**Hannan-Quinn Criterion:**	-3.814
F-statistic:	0.737	**Durbin-Watson Stat:**	1.950
Prob(F-stat.):	0.781		

Table 9 | Correlogram squared residuals

Sample (adjusted): 2004M10 2017M06
Qstatistic prob. Adj. for 20 dynam. Reg.



Autocorrelation	Partian Correlation		AC	PAC	Q-Stat	Prob*
		1	0.057	0.057	0.5030	0.478
		2	-0.064	-0.068	11.509	0.562
		3	-0.076	-0.069	20.604	0.560
		4	-0.113	-0.110	40.801	0.395
		5	-0.035	-0.033	42.762	0.510
		6	-0.004	-0.021	42.786	0.639
		7	0.086	0.086	54.668	0.603
		8	-0.023	-0.050	55.503	0.697
		9	0.071	0.079	63.898	0.700
		10	-0.079	-0.089	74.131	0.686
		11	-0.066	-0.036	81.487	0.700
		12	-0.037	-0.040	83.745	0.755
		13	0.005	0.008	83.783	0.818
		14	-0.048	-0.085	87.635	0.846
		15	0.006	0.003	87.696	0.889
		16	-0.011	-0.052	87.909	0.922
		17	-0.020	-0.007	88.572	0.945
		18	0.011	-0.014	88.799	0.962
		19	0.039	0.048	91.454	0.971
		20	0.008	-0.014	91.555	0.981
		21	-0.037	-0.027	94.058	0.986
		22	-0.031	-0.046	95.814	0.990
		23	-0.078	-0.062	10.682	0.986
		24	-0.007	-0.024	10.691	0.991
		25	0.002	-0.022	10.692	0.994
		26	0.063	0.031	11.429	0.996
		27	-0.001	-0.031	11.429	0.996
		28	0.013	0.132	14.733	0.981
		29	-0.043	-0.058	15.082	0.984
		30	-0.018	-0.036	15.147	0.989
		31	0.005	0.036	15.152	0.992
		32	-0.039	-0.010	15.443	0.995
		33	-0.049	-0.048	15.913	0.995
		34	0.016	0.029	15.976	0.993
		35	0.176	0.126	22.180	0.955
		36	-0.103	-0.112	24.316	0.931

4.3.5. Multicollinearity Test

To assess multicollinearity in the model, we performed the Variance Inflation Factor (VIF) test, which identifies whether any of the predictors are highly correlated with each other. VIF is calculated as:

$$VIF_{\mathrm{j}} = \frac{1}{1-R_j^2}, \tag{9}$$

where R_j^2 is the R-squared value from regression of the j-th predictor on all the other predictors in the model.

Table 10 | Variance Inflation Factor

Variance inflation Factors
Sample (adjusted): 2004M10 2017M06
Included observations: 153

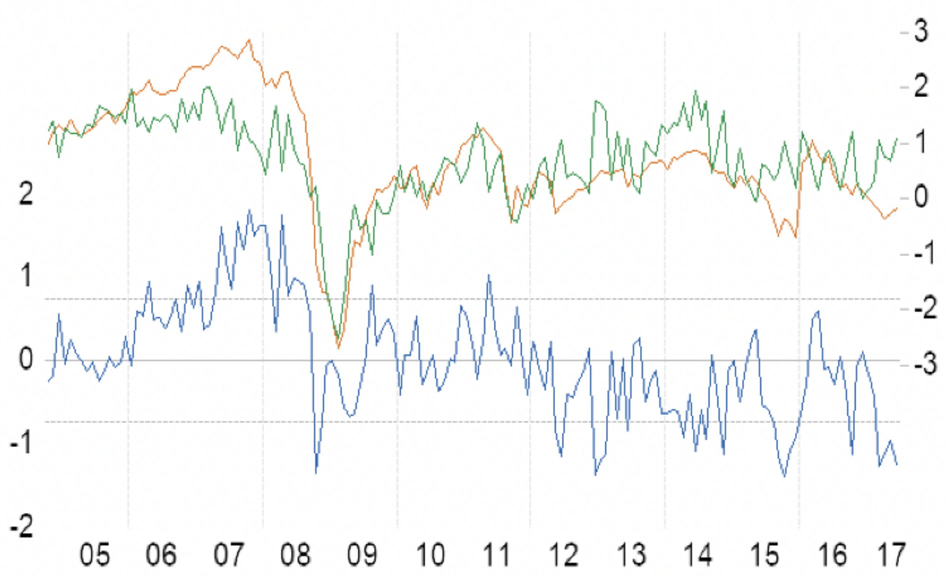
Variable	Coefficient Varience	Uncentered VIF	Centered VIF
C	0.00	49.53	NA
$GECI_t$	0.00	3.14	3.05
WD_{t-7}	0.00	9.85	1.34
WSJ_{t-1}	60.41	20.69	1.77
GFU_t	0.00	4.21	4.21
CFE_{t-2}	3.55E-12	1.76	1.50
$\Delta(DGS10_{t-12})$	0.00	1.15	1.15
$\Delta(CPI_{t-4})$	0.00	1.58	1.25
ET_{t-4}	0.00	12.68	1.35
$\Delta(LOG(SNP_{t-7}))$	0.12	1.346	1.33
$\Delta(GEPU_{t-1})$	2.40E-07	1.12	1.12
$USBY_{t-3}$	0.13	9.52	1.75
$LOG(USS_{t-11})$	0.00	1.62	1.46
$\Delta(IPCC_{t-20})$	2.08E-03	1.20	1.20
VIX_{t-1}	1.07E-05	31.55	5.68
CT_{t-3}	0.00	15.68	1.68
CS_{t-1}	0.00	6.04	1.77
$GFURF_{t-6}$	0.00	3.38	2.94
$GFUCSF_{t-2}$	0.00	7.75	7.51
$\Delta(GDP_t)$	2.42E-08	1.39	1.28
$USCP_{t-2}$	0.00	3.36	1.57

Table 11 Provides the VIF test in order to test the model for multicollinearity. Since the values of the Centered VIF values are lower than 10, we conclude that there is no evidence of multicollinearity.

4.4. In - Sample Forecast

In this section we performed an in-sample forecast to assess the predictability of climate related risks on GFCy. We conducted two forecasts, each for a different period for all of the three models. The first period is from 2016M01 to 2017M06 (the last eighteen months of the dataset) and the second period is from 2017M01 to 2017M06 (the last six months of the dataset). We analyzed the predictability by assessing Root Meean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percent Error (MAPE).

Figure 2 | Residual, Actual, Fitted



Note: Figure 2 presents with the green line the GFCy, the orange line presents the predicted values of GFCy, while the blue line presents the residuals. Because GFCy is non-stationary, we took first differences to ensure stationarity, which is necessary for analyzing and modeling the data.

4.4.1. Criteria Calculation

The RMSE can be calculated as:

$$RMSE = \sqrt{h^{-1} \sum_{t=1}^{h} (y_t - \hat{y}_t)^{\ 2}}, \tag{10}$$

$$MAE = h^{-1} \sum_{t=1}^{h} |y_t - \hat{y}_t|, \tag{11}$$

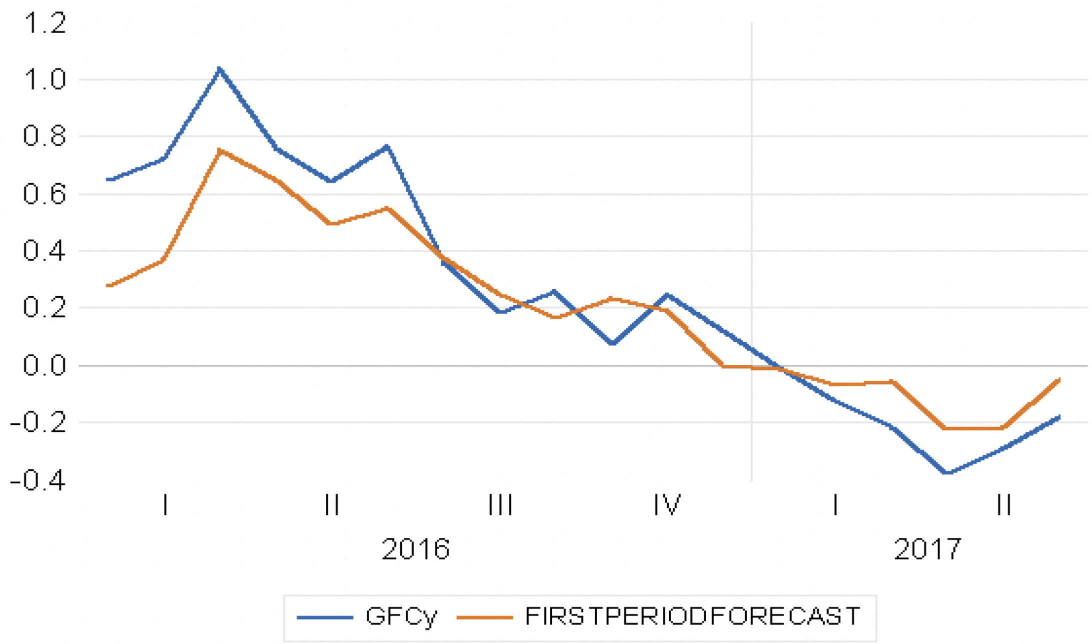
$$MAPE = 100h^{-1} \sum_{t=1}^{h} \left| \frac{y_t - \hat{y}_t}{y_t} \right|, \tag{12}$$

where $\hat{y}_t$ is forecasted value of the dependent variable, h is the size of the sample that is used for the forecast, $\bar{y}$ and $\overline{\hat{y}_t}$ are the mean of the y and $\hat{y}_t$.

The model that provides the lowest value in the criteria RMSE, MAE and MAPE has the best predictability.

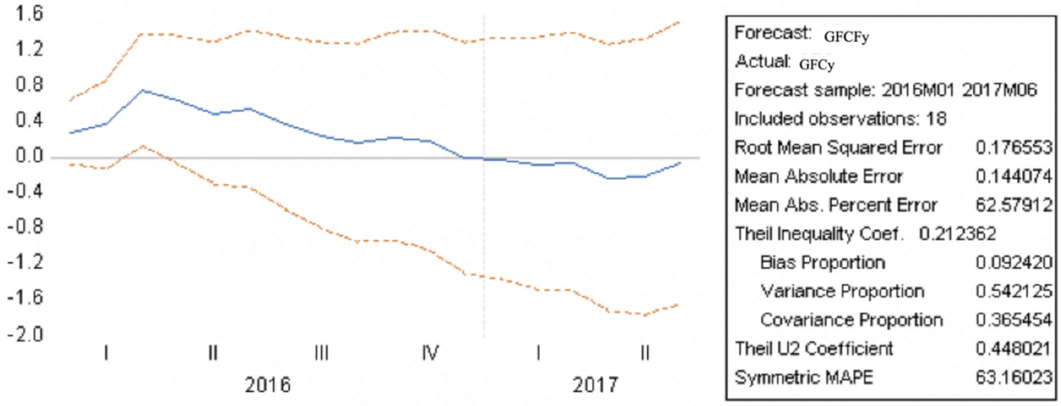
In this section we provide the graphs only of the best fitting model (model 1) and we compare the criteria RMSE, MAE and MAPE of the three models.

Figure 3 | Forecast Graph 2016M01 - 2017M06



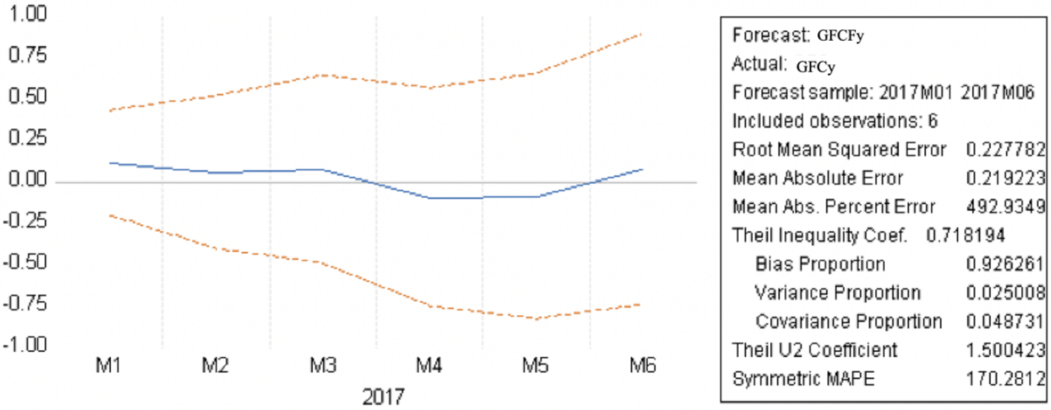
Note: Figure 3 illustrates the graph of Forecast with the graph of the dependent variable GFCy. The blue line presents the GFCy while the orange presents the forecast of model 1.

Figure 4 | Model 1 Forecast 2016M01 - 2017M06 First Period



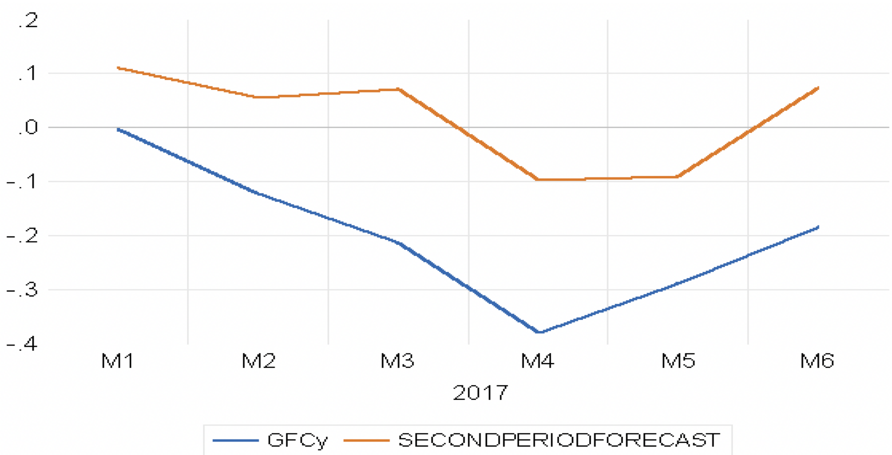
Note: Figure 4 illustrates the forecast of GFCy the first period of model 1.

Figure 5 | Model 1 Forecast 2017M01 - 2017M06 Second Period



Note: Figure 5 illustrates the forecast of GFCy in the second period of model 1.

Figure 6 | Forecast Graph 2017M01 - 2017M06



Note: Figure 3 illustrates the graph of Forecast with the graph of the dependent variable GFCy. The blue line presents the GFCy while the orange presents the forecast of model 1.

Table 11 | RMSE, MAE and MAPE Results

	2016M01 - 2017M06			2017M01 - 2017M06		
	RMSE	**MAE**	**MAPE**	**RMSE**	**MAE**	**MAPE**
Model 1	0.17	0.14	62.57	0.22	0.21	492.93
Model 2	0.29	0.25	245.37	0.35	0.33	568.70
Model 3	0.34	0.28	388.54	0.26	0.22	189.31

Table 11 provides the results of RMSE, MAE and MAPE. for model 1 in the first period RMSE is equal 0.17, MAE is 0.14 and MAPE is 62.57. For model 2 the RMSE is 0.29, MAE is 0.25 and MAPE is 245.37. RMSE, MAE and MAPE for model 3 is 0.34, 0.28 and 388.54, respectively. Also, in the second period the model 1 outperforms the other two models. The RMSE for model 1 in the second period is 0.22, MAE is 0.21 and MAPE is 492.93. Model 2 RMSE is 0.35, MAE is 0.33 and MAPE 568.70. For model 3 RMSE is 0.26 MAE is 0.22 and MAPE is 189.31. Among the three models, model 1 demonstrates the best predictability, in both periods.

The accuracy of the model 1 is higher, with lower errors (RMSE, MAE, MAPE), as the model was estimated in the stationary field of first differences. When the forecasts are converted to the GFCy level, the errors increase due to the accumulation of errors from the first differences. Model 1, achieved in the first period of the forecast a MAE of 0.14, and in the second forecasted period a MAE of 0.21, indicating that the predictions are, on average, close to the actual observed values. This suggests that the model is effective in capturing the underlying relationship between climate-related risks and the GFCy. While the model provides a reasonable approximation, there is room of improvement in capturing the dynamics of the GFCy.

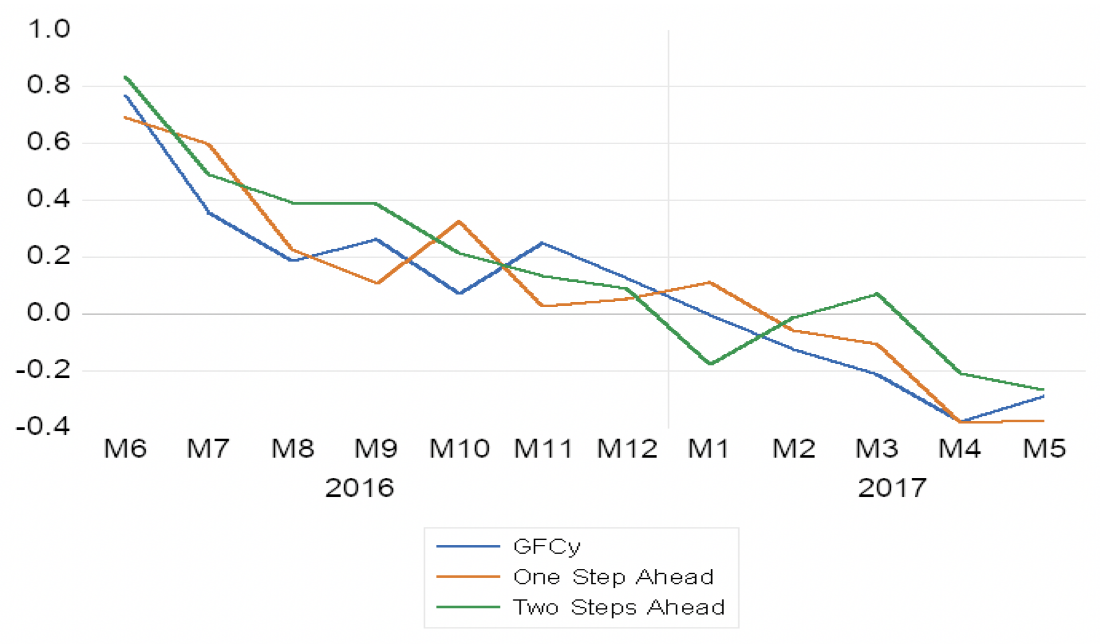
4.4.2. Step Ahead Forecasting

For the h step ahead forecast[13] we restructure the model to:

[13] The model is extended to generate forecasts for $t + 1, \dots, t + 4$.

$$\Delta(GFCy_{t+h}) = \beta_0 + \sum_{i=1}^{n} \beta_i X_{i,t+h}$$

Figure 7 | Step Ahead Forecasting



Note: *Figure 6 provides the graph of the one step ahead and two steps ahead forecast.*

Table 11.1 | RMSE, MAE and MAPE Results Step Ahead

	RMSE	**MAE**	**MAPE**
One Step Ahead	0.13	0.13	211.79
Two Steps Ahead	0.13	0.12	280.41
Three Steps Ahead	0.15	0.14	303.80
Four Steps Ahead	0.17	0.15	321.05

Table 12 provides the RMSE, MAE and MAPE of the steps ahead forecast. Across all three metrics the model's performance deteriorates as the prediction steps increase. The "One Step Ahead" forecast is the most accurate, which is typical since the model has the most recent data available and thus is more likely to make precise predictions. The results show that the model is more effective for short-term predictions but struggles with long-term forecasting.

5. | Theoretical Framework

In 1992, William Nordhaus introduced[14] the Dynamic Integrated Climate-Economy (DICE) model helps to understand the economic implications of climate change. The DICE model examines the relationship between economic growth and climate change. The model is a combination of the economic theory and climate science to assess how different levels of greenhouse gas emissions impact both economy and the environment, and it also analyzes the optimal policy responses to climate change.

N. Stern (2006) released a report for the Government of United Kingdom, in which Stern argues that the slower the intervention on climate change, the greater the economic cost of combating it. He also suggests that the impact of climate change on the Gross Domestic Product (GDP) might be significant as it can be reduced by 20% by the end of the century. Moreover, the report suggest that poorer nations might suffer in terms of economic losses because of climate change.

Sinn (2008) spoke of a phenomenon that arises from the climate polices, that aim to reduce the use of fossil fuels over time, but, the resource owners might anticipate that the demand of their fossil fuels will decrease in the future due to these policies, leading them to sale of fossil fuels in the present. This phenomenon is described as the Green Paradox.

Richard S. J. Tol (2009) in his study provided a comprehensive review of the economic impacts of climate change by analyzing the literature of both costs of climate change and the benefits of mitigation. The study examines various methodologies for estimating the economic consequences of climate change, mainly focusing on the long-term of GDP, agriculture etc. The paper suggests that the cost of climate change to the global economy might be uncertain but might also be substantial. For example, an increase in the temperature of 1°C, the GDP might reduce from 1% to 5%. Tol also focuses on the social cost of carbon (SCC), finding that the optimal carbon price should be modest, rather than high values.

In his book, Jeffrey D. Sachs, "The Age of Sustainable Development" (2015) presented the climate change as «the greatest global challenge of the 21st century». Sachs argues that climate change is a main issue in sustainable development and that's because of its impacts such as rising sea levels, extreme weather events and food

[14] Since then, the model has undergone multiple updates and refinements.

security challenges threating both human societies and natural ecosystems. Sachs points out the need of reducing the greenhouse gas emissions and mitigating global warming. Moreover, he mentions the need of economic transition to a green economy, advocating for a transition to a low-carbon economy through investments in green technologies, such as renewable energy, clean transportation and energy efficiency.

Dafermos *et al.* (2018) studied the impact of climate change on the financial stability and on the monetary policy. They focus on the impacts that occur on financial assets and the financial position of firms and banks. The review suggests that climate change may harm even more the financial and non-financial sector when there is a reduction in the capital and the profitability of the firms. Moreover, climate change could result in a shift in the portfolio composition, potentially leading to gradual decrease in the value of corporate bonds. Additionally, climate-driven financial instability could hinder credit growth, intensifying the negative effects of climate change on economic activity. Finally, a green corporate quantitative easing (QE) program could help mitigate climate-related financial instability and limit global warming.

Dennis, Benjamin N. (2019) examines the literature that connects the climate change with financial policy. In his study, Dennis explores the impacts of climate related risks on the financial markets, institutions and regulatory frameworks, providing an overview of the key issues, challenges and policy responses that are related to climate change and finance. The study suggests that financial markets are not adequately priced for climate risks, leading to a mispricing of assets which might lead to an instability of the financial systems. Dennis, refers to studies that suggest carbon-intensive industries and regions vulnerable to climate risks facing greater risks, leading to a capital misallocation and a shift in investor behavior. Dennis, also points out that there is a growing interest in green finance, including the development of green bonds and sustainable investment strategies, because of the investors try to mitigate climate risk and align their portfolios with environmental goals. Overall, the review points the need of integrating climate related risks into financial systems, calling for stronger disclosure to practices, enhanced regulatory frameworks and more robust risk managements strategies within financial institutions.

Recent studies argue that countries with high temperatures have a greater negative impact on their economic development, which is observed mainly through lower investments, a decrease in the amount of production in the agricultural and industrial sectors. Finally, it is observed that through economic development, countries with higher wage levels are economically more shielded from the effects of temperature increases compared to countries where wages are lower (Acevedo, 2020).

6 | Discussion

The purpose of this thesis was to examine the relationship of climate change and its predictability on GFCy, to contribute to the literature and to encourage readers to engage with climate change. Additionally, the study examines the connection of climate related risks with the GFCy.

Although, model 1, is a simple model we see that it can predict the GFCy satisfactorily. While the model performs well for short-term forecasting, improving its ability to capture long term trends and incorporate external factors or more complex methodologies could enhance its forecasting ability, particularly for multi-step ahead predictions.

The review shows that there is a highly negative connection of physical risk with the GFCy. This finding is consistent with similar studies in the literature, which demonstrates that physical risk mainly affects negatively the economies and the financial markets. More specifically, the study suggests that water & drought impacts the GFCy negatively seven months after the event. Moreover, extreme temperatures effect the GFCy also negatively but four months after their occurrences. The most significant effect on GFCy is from the WSJ index occurring just the next month, indicating a strong connection between the investors' concern and climate risk which impacts are reflected to the GFCy. On the other hand, the transition risk shows a positive impact on the GFCy. The study suggests that climate summits, carbon tax and IPCC's reports have positive connection with the GFCy, one -period lag, three -periods lag and twenty -periods lag respectively. Climate change mitigation and transition to a green economy can be interpreted as opportunities for growth, innovation and capital accumulation. The future regulatory actions may lead businesses to invest in cleaner technologies creating new fields of economic expansion. In other words, climate policies motivate investments in sectors that promote long-term sustainable growth. On the other side, USCP has a low negative impact on the GFCy. This might be because of the green paradox, fossil fuels owners when expect stricter climate policies in the future, they may accelerate their extraction and use of fossil fuels in the present to maximize profits before the policy takes effect. Moreover, the climate policies might also be a deterrent to investment.

Physical risk has been shown to negatively impact the financial markets and economies, increasing the volatility and the instability. The adverse effects of physical risks can affect negatively the market operations, the confidence of the investors, the economic growth, etc. Leading to a significant financial loss, disruption in the demand and supply chains which in turn weaken the economic resilience. These risks have been documented in the literature where numerous studies highlight the detrimental effects pf physical risks on both financial markets' performance and broader the economic stability.

Transition risk presents significant opportunities for innovation, market growth and economic resilience. This can be possible as governments implement stricter environmental policies and industries adopt sustainable technologies, new markets and investments are emerging. Leading to the development of green technologies, renewable energy sectors and sustainable financial instruments, driving economic diversification and long-term growth. Literature highlights the potential positive changes that occur from the transition risks. Several studies note that financial markets that proactively adapt to environmental regulations are often better positioned for future growth. Environmental policies are not only expected to reduce the environmental harm but also contribute to more stable, forward-looking economic structures.

The urgency of addressing climate risk has never been clearer. Global warming and extreme weather events have already started harming the ecosystems and economies. Governments must adopt effective in order to prevent the irreversible damages that is caused from the climate change. Despite ongoing international efforts, current climate policies have failed to reduce global warming. It is more than needed to redefine the ongoing polices with approach which will prevent the catastrophic environmental and economic consequences.

The following political recommendations outline a comprehensive approach to climate policy, aiming to balance environmental sustainability with economic growth. Carbon taxes might play a significant role for addressing climate change. Rising the carbon taxes may encourage the adoption of cleaner technologies and will lead to a reduction in emissions. Technological innovation and research have their crucial impact on the climate change. Investments in clean energy research and development (R&D) mainly in sectors like energy production, storage, etc. will be important in long term of dealing with climate change. Decision makers should keep in my that climate change is an international problem, decisions should be taken globally and marked placed in order to avoid turbulence in the markets. By implementing these strategies, policymakers can guide the world toward a more resilient and low-carbon future.

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., & Topalova, P. (2020). The effects of weather shocks on economic activity: What are the channels of impact? Journal of Macroeconomics, 65, Article 103207.

Ardia *et al*. (2023),"Climate Change Concerns and Performance of Green vs. Brown Stocks" *Management Science*, vol. 69, no. 12, pp. 7607–7632.

Adrien B., Diego R. Känzig, (2024), "The Macroeconomic Impact of Climate Change: Global vs. Local Temperature," NBER Working Papers 32450 *National Bureau of Economic Research*, Inc.

Agrippino S. M, & Rey H., (2021). "The Global Financial Cycle," NBER Working Papers 29327, *National Bureau of Economic Research, Inc.*

Baumeister, C., Korobilis, D., & Lee, T. K. (2020). Energy markets and global economic conditions. *Review of Economics and Statistics*, 104, 828–844.

Caggiano, G., & Castelnuovo, E. (2023). Global financial uncertainty. *Journal of Applied Econometrics*, 38(3), 432–449.

Cerutti, E., Claessens, S. (2024), The Global Financial Cycle: Quantities Versus Prices. *IMF Working Paper* No. 2024/158.

Colacito, R., Hoffmann B., Toan P., (2016). "Temperature and Growth: A Panel Analysis of the United States", *IDB Publications* (Working Papers) 7654, *Inter-American Development Bank*

Cook. J, Orekses N., Doran P., Anderegg W. R L. (2016). "Consensus on Consensus: A Synthesis of Consensus Estimates on Human-Caused Global Warming. *Environmental Research Letters* 11(4):048002.

Dafermos, Y., Nikolaidi, M., & Galanis, G. (2017). Climate change, financial stability and monetary policy. *Journal of Financial Stability*, 45(2), 100-115.

Dennis B., (2022). "Climate Change and Financial Policy: A Literature Review," Finance and Economics Discussion Series 2022-048, *Board of Governors of the Federal Reserve System (U.S.).*

Doran P. T., Zimmerman M. (2011). "Examining the Scientific Consensus on Climate Change." *Transaction American Geophysical Union*, (3): 22-25.

Faccini R. and Matin R., Skiadopoulos G. (2023). Dissecting Climate Risks: Are they Reflected in Stock Prices? *Journal of Banking and Finance*.

Gavriilidis, K. (2021), Measuring Climate Policy Uncertainty. Available at *SSRN 3847388.*

Brookes, G. H, Taraz V, Halliday SD (2023). The impact of weather shocks on employment outcomes: evidence from South Africa. *Environment and Development Economics.;28(3):285-305*.

He, Mengxi, Zhang, Y., (2022). "Climate policy uncertainty and the stock return predictability of the oil industry," *Journal of International Financial Markets, Institutions and Money, Elsevier*, vol. 81(C).

Ho, T. (2022). Climate change news sensitivity and mutual fund performance. *International Review of Financial Analysis*, 83, Article 102331.

Hong, H., Weikai F. L., Xu J. (2019). "Climate risks and market efficiency". 265-281, *Journal of econometrics*.

Kjellstrom T., Holmer, I. & Lemke, B., (2009). Workplace heat stress, health and productivity – An increasing challenge for low and middle-income countries during climate change. *Global health action*.

Liu, T. Y. & Lin Y. (2023). "Does global warming affect unemployment? International evidence," *Economic Analysis and Policy, Elsevier*, vol. 80(C) pages 991-1005.

Lynas M., Houlton B. Z. and Perry S. (2021). "Greater than 99% consensus on human caused climate change in the peer-reviewed scientific literature". *Environ. Res. Lett.* 16 114005.

Newman, R., Noy, I. (2023). The global costs of extreme weather that are attributable to climate change. *Nature Communications* 14, 6103.

Ngepah, N.; Conselho M. R. (2022) The Impact of Climate Change on Gender Inequality in the Labour Market: A Case Study of South Africa. Sustainability, 14, 13131, *Sustainability, MDPI*, vol. 14(20).

Nordhaus, W. (1994). Managing the Global Commons: The Economics of Climate Change, Cambridge, MA, *MIT Press*, USA.

Nordhaus, W. (2007). "A Review of the Stern Review on the Economics of Climate Change." *Journal of Economic Literature*, 45 (3): 686-702.

Nordhaus, W. (2019). "Climate Change: The Ultimate Challenge for Economics." *American Economic Review*, 109 (6): 1991-2014.

Nordhaus, W. (2017). "Evolution of Assessments of the Economics of Global Warming: Changes in the DICE model, 1992 – 2017". *National Bereau of Economic Research.* WP: 23319.

Moore, F. & Lobell, D. (2014). Adaptation potential of European agriculture in response to climate change. *Nature Climate Change*. 4. 614.

Pasnicu, D., Ciuca, V. (2020). Green procurement implications on the labor market in the context of the transition to the green economy, *Amfiteatru Economic Journal*, ISSN 2247-9104, The Bucharest University of Economic Studies, Buc.

Pycroft, J., Abrell, J., and Ciscar, J.-C. (2015). The global impacts of extreme sea-level rise: A comprehensive economic assessment. *Environmental and Resource Economics*, pages 1–29.

Rey, H., (2013). "Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence.", Proceedings - Economic Policy Symposium - Jackson Hole, *Federal Reserve of Kansas City Economic Symposium*, p 285-333.

Sinn, H.-W. (2008). Public policies against global warming: A supply side approach. *International Tax and Public Finance* 15 (4): 360–94.

Stevanovic, M., Popp, A., Lotze-Campen, H., Dietrich, J. P., Müller, C., Bonsch, M., Schmitz, C., Bodirsky, B. L., Humpen¨ oder, F., & Weindl, I. (2016). "The impact of high-end climate change on agricultural welfare". *Science Advances*, 2, Article e150145.

Engle R. F., Giglio S., Kelly B, Lee H., Stroebel J., (2020). Hedging Climate Change News, *The Review of Financial Studies*, Volume 33, Issue 3, Pages 1184–1216.

Sachs, J. D. (2015). The age of sustainable development. Columbia University Press.

Salisu A. A. & Philip C. O., Abdulsalam A. S., (2023). "Geopolitical risk and global financial cycle: Some forecasting experiments," *Journal of Forecasting, John Wiley & Sons, Ltd.,* vol. 42(1), pages 3-16, January.

Stern, N. (2006). The Economics of Climate Change: The Stern Review. *Cambridge University Press*.

Tedeschi, M., Foglia, M., Bouri, E., & Dai, P.-F. (2024). How does climate policy uncertainty affect financial markets? Evidence from Europe. *Economics Letters*, 234(111443).

Tol, R. S. J. (2009). "The Economic Effects of Climate Change." *Journal of Economic Perspectives*, 23 (2): 29–51.

Westerlund, J., Narayan, P. (2015). A Random Coefficient Approach to the Predictability of Stock Returns in Panels. *Journal of Financial Econometrics*, 13, 605-664.

Westerlund, Joakim, Narayan, P., (2012). "Does the choice of estimator matter when forecasting returns?" *Journal of Banking & Finance, Elsevier,* vol. 36(9), pages 2632-2640.

Wilson, Daniel J. (2017). “The Impact of Weather on Local Employment: Using Big Data on Small Places” *Federal Reserve Bank of San Francisco Working Paper* 2016-21.

Schlenker W. & Hanemann M. W. & Fisher A. C., (2006). "The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions," *The Review of Economics and Statistics, MIT Press,* vol. 88(1), pages 113-125,

Xu, X., Huang, S., & Lucey, B. (2023). The impacts of climate policy uncertainty on stock markets: Comparison between China and the US[J]. *International Review of Financial Analysis,* 88(5), Article 102671.

Yang Y., Huang C., Zhang Y. (2023). “Decomposing Climate Risks in Stock Markets”. *International Monetary Fund Working Papers* 2023, 141.

Ye, L., (2022). The effect of climate news risk on uncertainties. *Technol. Forecast. Soc. hange* 178, 121586.

Appendix

Table 12 | Stationarity of Variables Augmented Dickey-Fuller ADF-Test

Water and Drought

Null Hypothesis: WD has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.438560	0.0000
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(WD)
Method: Least Squares
Date: 11/29/24 Time: 15:13
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
WD(-1)	-0.427681	0.078639	-5.438560	0.0000
D(WD(-1))	-0.216576	0.075752	-2.858994	0.0048
C	0.339015	0.065468	5.178344	0.0000

R-squared	0.303673	Mean dependent var	0.004864
Adjusted R-squared	0.295432	S.D. dependent var	0.354402
S.E. of regression	0.297480	Akaike info criterion	0.430349
Sum squared resid	14.95555	Schwarz criterion	0.485247
Log likelihood	-34.00998	Hannan-Quinn criter.	0.452622
F-statistic	36.85104	Durbin-Watson stat	2.036557
Prob(F-statistic)	0.000000		

Global Economic Conditions Indicator

Null Hypothesis: GECI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.961302	0.0020
Test critical values:	1% level	-3.468295	
	5% level	-2.878113	
	10% level	-2.575684	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GECI)
Method: Least Squares
Date: 11/29/24 Time: 15:10
Sample (adjusted): 2003M02 2017M06
Included observations: 173 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GECI(-1)	-0.168167	0.042452	-3.961302	0.0001
C	-0.004742	0.018930	-0.250506	0.8025

R-squared	0.084052	Mean dependent var	0.001969
Adjusted R-squared	0.078696	S.D. dependent var	0.258358
S.E. of regression	0.247983	Akaike info criterion	0.060584
Sum squared resid	10.51578	Schwarz criterion	0.097038
Log likelihood	-3.240473	Hannan-Quinn criter.	0.075373
F-statistic	15.69192	Durbin-Watson stat	2.148783
Prob(F-statistic)	0.000109		

Capital Flow Equity

Null Hypothesis: CFEQUITY has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.639930	0.0000
Test critical values:	1% level	-3.468295	
	5% level	-2.878113	
	10% level	-2.575684	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CFEQUITY)
Method: Least Squares
Date: 11/29/24 Time: 15:19
Sample (adjusted): 2003M02 2017M06
Included observations: 173 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CFEQUITY(-1)	-0.704449	0.073076	-9.639930	0.0000
C	2326.625	601.6076	3.867347	0.0002

R-squared	0.352097	Mean dependent var	37.50424
Adjusted R-squared	0.348308	S.D. dependent var	9006.128
S.E. of regression	7270.418	Akaike info criterion	20.63251
Sum squared resid	9.04E+09	Schwarz criterion	20.66896
Log likelihood	-1782.712	Hannan-Quinn criter.	20.64730
F-statistic	92.92825	Durbin-Watson stat	2.077198
Prob(F-statistic)	0.000000		

Climate Summit

Null Hypothesis: CS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.214363	0.0000
Test critical values:	1% level	-3.468295	
	5% level	-2.878113	
	10% level	-2.575684	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CS)
Method: Least Squares
Date: 11/29/24 Time: 15:28
Sample (adjusted): 2003M02 2017M06
Included observations: 173 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CS(-1)	-0.598358	0.072843	-8.214363	0.0000
C	0.354136	0.050761	6.976514	0.0000

R-squared	0.282946	Mean dependent var	0.009267
Adjusted R-squared	0.278753	S.D. dependent var	0.441888
S.E. of regression	0.375279	Akaike info criterion	0.889202
Sum squared resid	24.08273	Schwarz criterion	0.925656
Log likelihood	-74.91595	Hannan-Quinn criter.	0.903991
F-statistic	67.47575	Durbin-Watson stat	2.042591
Prob(F-statistic)	0.000000		

Carbon Tax

Null Hypothesis: CT has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.376750	0.0131
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CT)
Method: Least Squares
Date: 11/29/24 Time: 15:27
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CT(-1)	-0.199692	0.059137	-3.376750	0.0009
D(CT(-1))	-0.419709	0.070682	-5.937960	0.0000
C	0.169119	0.050287	3.363052	0.0010

R-squared	0.312318	Mean dependent var	0.007394
Adjusted R-squared	0.304179	S.D. dependent var	0.268855
S.E. of regression	0.224267	Akaike info criterion	-0.134667
Sum squared resid	8.500005	Schwarz criterion	-0.079769
Log likelihood	14.58136	Hannan-Quinn criter.	-0.112393
F-statistic	38.37648	Durbin-Watson stat	2.071468
Prob(F-statistic)	0.000000		

Extreme Temperature

Null Hypothesis: ET has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.443353	0.0000
Test critical values:	1% level	-3.468295	
	5% level	-2.878113	
	10% level	-2.575684	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ET)
Method: Least Squares
Date: 11/29/24 Time: 15:20
Sample (adjusted): 2003M02 2017M06
Included observations: 173 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ET(-1)	-0.492326	0.066143	-7.443353	0.0000
C	0.472339	0.067162	7.032795	0.0000

R-squared	0.244711	Mean dependent var	0.005498
Adjusted R-squared	0.240294	S.D. dependent var	0.362511
S.E. of regression	0.315969	Akaike info criterion	0.545145
Sum squared resid	17.07198	Schwarz criterion	0.581599
Log likelihood	-45.15506	Hannan-Quinn criter.	0.559935
F-statistic	55.40351	Durbin-Watson stat	2.107994
Prob(F-statistic)	0.000000		

Global Financial Uncertainty

Null Hypothesis: GFU has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.616846	0.0064
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GFU)
Method: Least Squares
Date: 11/29/24 Time: 15:18
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GFU(-1)	-0.099987	0.027645	-3.616846	0.0004
D(GFU(-1))	0.345903	0.072014	4.803294	0.0000
C	-0.002058	0.016958	-0.121386	0.9035

R-squared	0.153346	Mean dependent var	-0.005015
Adjusted R-squared	0.143327	S.D. dependent var	0.240150
S.E. of regression	0.222274	Akaike info criterion	-0.152520
Sum squared resid	8.349599	Schwarz criterion	-0.097622
Log likelihood	16.11674	Hannan-Quinn criter.	-0.130247
F-statistic	15.30466	Durbin-Watson stat	1.985840
Prob(F-statistic)	0.000001		

United States Bond Yields

Null Hypothesis: USBY has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.842692	0.0000
Test critical values:	1% level	-3.468295	
	5% level	-2.878113	
	10% level	-2.575684	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(USBY)
Method: Least Squares
Date: 11/29/24 Time: 15:22
Sample (adjusted): 2003M02 2017M06
Included observations: 173 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
USBY(-1)	-0.627527	0.070966	-8.842692	0.0000
C	0.058990	0.007457	7.910695	0.0000

R-squared	0.313785	Mean dependent var	-0.000343
Adjusted R-squared	0.309773	S.D. dependent var	0.051508
S.E. of regression	0.042793	Akaike info criterion	-3.453397
Sum squared resid	0.313140	Schwarz criterion	-3.416942
Log likelihood	300.7188	Hannan-Quinn criter.	-3.438607
F-statistic	78.19320	Durbin-Watson stat	2.177076
Prob(F-statistic)	0.000000		

United States Stock

Null Hypothesis: USS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.772212	0.0001
Test critical values:	1% level	-3.468295	
	5% level	-2.878113	
	10% level	-2.575684	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(USS)
Method: Least Squares
Date: 11/29/24 Time: 15:24
Sample (adjusted): 2003M02 2017M06
Included observations: 173 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
USS(-1)	-0.234575	0.049154	-4.772212	0.0000
C	0.219798	0.057346	3.832862	0.0002

R-squared	0.117529	Mean dependent var	-0.006163
Adjusted R-squared	0.112368	S.D. dependent var	0.451639
S.E. of regression	0.425508	Akaike info criterion	1.140429
Sum squared resid	30.96081	Schwarz criterion	1.176883
Log likelihood	-96.64712	Hannan-Quinn criter.	1.155218
F-statistic	22.77401	Durbin-Watson stat	2.050646
Prob(F-statistic)	0.000004		

Volatility Index

Null Hypothesis: VIXCLS has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.043535	0.0330
Test critical values:	1% level	-3.468749	
	5% level	-2.878311	
	10% level	-2.575791	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(VIXCLS)
Method: Least Squares
Date: 11/29/24 Time: 15:26
Sample (adjusted): 2003M04 2017M06
Included observations: 171 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VIXCLS(-1)	-0.111332	0.036580	-3.043535	0.0027
D(VIXCLS(-1))	0.217874	0.074174	2.937319	0.0038
D(VIXCLS(-2))	-0.193785	0.075430	-2.569056	0.0111
C	2.004932	0.755750	2.652904	0.0088

R-squared	0.132905	Mean dependent var	-0.117665
Adjusted R-squared	0.117328	S.D. dependent var	4.050867
S.E. of regression	3.805815	Akaike info criterion	5.534051
Sum squared resid	2418.866	Schwarz criterion	5.607540
Log likelihood	-469.1614	Hannan-Quinn criter.	5.563870
F-statistic	8.532351	Durbin-Watson stat	1.969915
Prob(F-statistic)	0.000026		

Wall Street Journal Index

Null Hypothesis: WSJ has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.437642	0.0000
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(WSJ)
Method: Least Squares
Date: 11/29/24 Time: 15:16
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
WSJ(-1)	-0.442113	0.081306	-5.437642	0.0000
D(WSJ(-1))	-0.267420	0.074058	-3.610971	0.0004
C	0.002940	0.000558	5.267711	0.0000

R-squared	0.352471	Mean dependent var	9.30E-06
Adjusted R-squared	0.344808	S.D. dependent var	0.002310
S.E. of regression	0.001870	Akaike info criterion	-9.708361
Sum squared resid	0.000591	Schwarz criterion	-9.653462
Log likelihood	837.9190	Hannan-Quinn criter.	-9.686087
F-statistic	45.99606	Durbin-Watson stat	2.034650
Prob(F-statistic)	0.000000		

Global Financial Uncertainty Country Specific Factor

Null Hypothesis: GFUCSF has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.926871	0.0443
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GFUCSF)
Method: Least Squares
Date: 11/29/24 Time: 15:29
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GFUCSF(-1)	-0.069413	0.023716	-2.926871	0.0039
D(GFUCSF(-1))	0.338782	0.072358	4.681992	0.0000
C	0.017738	0.036875	0.481013	0.6311

R-squared	0.135702	Mean dependent var	-0.008715
Adjusted R-squared	0.125473	S.D. dependent var	0.505352
S.E. of regression	0.472586	Akaike info criterion	1.356092
Sum squared resid	37.74398	Schwarz criterion	1.410991
Log likelihood	-113.6239	Hannan-Quinn criter.	1.378366
F-statistic	13.26716	Durbin-Watson stat	2.002043
Prob(F-statistic)	0.000004		

United States Climate Policy

Null Hypothesis: USCP has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.026238	0.0000
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(USCP)
Method: Least Squares
Date: 11/29/24 Time: 15:35
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
USCP(-1)	-0.555067	0.092108	-6.026238	0.0000
D(USCP(-1))	-0.280796	0.075500	-3.719130	0.0003
C	0.364636	0.089875	4.057165	0.0001

R-squared	0.430499	Mean dependent var	-0.002764
Adjusted R-squared	0.423759	S.D. dependent var	1.165842
S.E. of regression	0.884997	Akaike info criterion	2.610823
Sum squared resid	132.3642	Schwarz criterion	2.665721
Log likelihood	-221.5308	Hannan-Quinn criter.	2.633097
F-statistic	63.87546	Durbin-Watson stat	2.076575
Prob(F-statistic)	0.000000		

Table 13 | Stationarity of Variables Augmented Dickey-Fuller First Differences ADF-Test

<u>Global Financial Cycle</u>

Null Hypothesis: GFC has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.590825	0.0968
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GFC)
Method: Least Squares
Date: 11/22/24 Time: 16:53
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GFC(-1)	-0.056144	0.021670	-2.590825	0.0104
D(GFC(-1))	0.249952	0.074252	3.366260	0.0009
C	0.039820	0.025940	1.535112	0.1266

R-squared	0.086233	Mean dependent var	0.003180
Adjusted R-squared	0.075419	S.D. dependent var	0.294874
S.E. of regression	0.283537	Akaike info criterion	0.334337
Sum squared resid	13.58642	Schwarz criterion	0.389235
Log likelihood	-25.75298	Hannan-Quinn criter.	0.356611
F-statistic	7.974308	Durbin-Watson stat	2.036874
Prob(F-statistic)	0.000490		

Global Financial Cycle First Difference

Null Hypothesis: D(GFC) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.38443	0.0000
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GFC,2)
Method: Least Squares
Date: 11/22/24 Time: 16:53
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GFC(-1))	-0.776479	0.074773	-10.38443	0.0000
C	0.002685	0.021980	0.122166	0.9029

R-squared	0.388129	Mean dependent var	0.000967
Adjusted R-squared	0.384530	S.D. dependent var	0.367437
S.E. of regression	0.288261	Akaike info criterion	0.361659
Sum squared resid	14.12605	Schwarz criterion	0.398258
Log likelihood	-29.10265	Hannan-Quinn criter.	0.376508
F-statistic	107.8364	Durbin-Watson stat	2.014650
Prob(F-statistic)	0.000000		

Market Yield on United States Treasury Securities at 10-Year Constant Maturity

Null Hypothesis: DGS10 has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.575469	0.4930
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DGS10)
Method: Least Squares
Date: 11/22/24 Time: 16:57
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DGS10(-1)	-0.024298	0.015423	-1.575469	0.1170
D(DGS10(-1))	0.222079	0.075050	2.959092	0.0035
C	0.070682	0.052389	1.349183	0.1791

R-squared	0.057823	Mean dependent var	-0.009976
Adjusted R-squared	0.046673	S.D. dependent var	0.216329
S.E. of regression	0.211221	Akaike info criterion	-0.254539
Sum squared resid	7.539790	Schwarz criterion	-0.199641
Log likelihood	24.89039	Hannan-Quinn criter.	-0.232266
F-statistic	5.185952	Durbin-Watson stat	1.932448
Prob(F-statistic)	0.006519		

Market Yield on United States Treasury Securities at 10-Year Constant Maturity First Difference

Null Hypothesis: D(DGS10) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.54415	0.0000
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DGS10,2)
Method: Least Squares
Date: 11/22/24 Time: 16:58
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(DGS10(-1))	-0.790365	0.074958	-10.54415	0.0000
C	-0.007849	0.016193	-0.484700	0.6285

R-squared	0.395403	Mean dependent var	0.000169
Adjusted R-squared	0.391847	S.D. dependent var	0.272029
S.E. of regression	0.212139	Akaike info criterion	-0.251587
Sum squared resid	7.650527	Schwarz criterion	-0.214988
Log likelihood	23.63649	Hannan-Quinn criter.	-0.236738
F-statistic	111.1791	Durbin-Watson stat	1.931847
Prob(F-statistic)	0.000000		

Global Economic Policy Uncertainty Index

Null Hypothesis: GEPUCURRENT has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.900035	0.3318
Test critical values:	1% level	-3.468980	
	5% level	-2.878413	
	10% level	-2.575844	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GEPUCURRENT)
Method: Least Squares
Date: 11/22/24 Time: 17:00
Sample (adjusted): 2003M05 2017M06
Included observations: 170 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GEPUCURRENT(-1)	-0.086751	0.045657	-1.900035	0.0592
D(GEPUCURRENT(-1))	-0.203755	0.079280	-2.570063	0.0111
D(GEPUCURRENT(-2))	-0.167517	0.078284	-2.139857	0.0338
D(GEPUCURRENT(-3))	-0.253879	0.076908	-3.301093	0.0012
C	10.31921	5.508050	1.873477	0.0628

R-squared	0.153951	Mean dependent var	0.202606
Adjusted R-squared	0.133441	S.D. dependent var	25.45293
S.E. of regression	23.69391	Akaike info criterion	9.197284
Sum squared resid	92631.25	Schwarz criterion	9.289513
Log likelihood	-776.7691	Hannan-Quinn criter.	9.234710
F-statistic	7.506056	Durbin-Watson stat	2.008865
Prob(F-statistic)	0.000014		

Global Economic Policy Uncertainty Index First Differences

Null Hypothesis: D(GEPUCURRENT) has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.52413	0.0000
Test critical values:	1% level	-3.468980	
	5% level	-2.878413	
	10% level	-2.575844	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GEPUCURRENT,2)
Method: Least Squares
Date: 11/22/24 Time: 17:00
Sample (adjusted): 2003M05 2017M06
Included observations: 170 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GEPUCURRENT(-1))	-1.765790	0.153225	-11.52413	0.0000
D(GEPUCURRENT(-1)...	0.505627	0.117488	4.303640	0.0000
D(GEPUCURRENT(-2)...	0.291541	0.074891	3.892871	0.0001
C	0.440263	1.832312	0.240277	0.8104

R-squared	0.638031	Mean dependent var	0.222066
Adjusted R-squared	0.631489	S.D. dependent var	39.33684
S.E. of regression	23.87946	Akaike info criterion	9.207163
Sum squared resid	94657.99	Schwarz criterion	9.280946
Log likelihood	-778.6089	Hannan-Quinn criter.	9.237103
F-statistic	97.53415	Durbin-Watson stat	2.028002
Prob(F-statistic)	0.000000		

Intergovernmental Panel on Climate Change

Null Hypothesis: IPCC has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.863126	0.0519
Test critical values:	1% level	-3.469214	
	5% level	-2.878515	
	10% level	-2.575899	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IPCC)
Method: Least Squares
Date: 11/22/24 Time: 17:01
Sample (adjusted): 2003M06 2017M06
Included observations: 169 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IPCC(-1)	-0.226639	0.079158	-2.863126	0.0047
D(IPCC(-1))	-0.399217	0.093150	-4.285746	0.0000
D(IPCC(-2))	-0.224540	0.088668	-2.532363	0.0123
D(IPCC(-3))	-0.348238	0.084245	-4.133618	0.0001
D(IPCC(-4))	-0.269738	0.074985	-3.597241	0.0004
C	0.180738	0.062604	2.887017	0.0044

R-squared	0.343495	Mean dependent var	0.005557
Adjusted R-squared	0.323357	S.D. dependent var	0.305006
S.E. of regression	0.250893	Akaike info criterion	0.107277
Sum squared resid	10.26041	Schwarz criterion	0.218398
Log likelihood	-3.064927	Hannan-Quinn criter.	0.152372
F-statistic	17.05689	Durbin-Watson stat	2.067155
Prob(F-statistic)	0.000000		

Intergovernmental Panel on Climate Change First Differences

Null Hypothesis: D(IPCC) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.15236	0.0000
Test critical values:	1% level	-3.469214	
	5% level	-2.878515	
	10% level	-2.575899	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IPCC,2)
Method: Least Squares
Date: 11/22/24 Time: 17:01
Sample (adjusted): 2003M06 2017M06
Included observations: 169 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(IPCC(-1))	-2.681976	0.220696	-12.15236	0.0000
D(IPCC(-1),2)	1.115401	0.178516	6.248194	0.0000
D(IPCC(-2),2)	0.766757	0.130294	5.884801	0.0000
D(IPCC(-3),2)	0.322985	0.074219	4.351794	0.0000
C	0.010234	0.019728	0.518764	0.6046

R-squared	0.749889	Mean dependent var	0.001656
Adjusted R-squared	0.743789	S.D. dependent var	0.506426
S.E. of regression	0.256339	Akaike info criterion	0.144511
Sum squared resid	10.77642	Schwarz criterion	0.237111
Log likelihood	-7.211139	Hannan-Quinn criter.	0.182090
F-statistic	122.9271	Durbin-Watson stat	2.101209
Prob(F-statistic)	0.000000		

S&P 500

Null Hypothesis: SNP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.348312	0.9802
Test critical values:	1% level	-3.468295	
	5% level	-2.878113	
	10% level	-2.575684	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SNP)
Method: Least Squares
Date: 11/22/24 Time: 17:00
Sample (adjusted): 2003M02 2017M06
Included observations: 173 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SNP(-1)	0.003336	0.009578	0.348312	0.7280
C	4.073179	14.35956	0.283656	0.7770

R-squared	0.000709	Mean dependent var	8.888497
Adjusted R-squared	-0.005135	S.D. dependent var	50.93572
S.E. of regression	51.06633	Akaike info criterion	10.71562
Sum squared resid	445928.6	Schwarz criterion	10.75208
Log likelihood	-924.9012	Hannan-Quinn criter.	10.73041
F-statistic	0.121321	Durbin-Watson stat	1.851778
Prob(F-statistic)	0.728034		

S&P 500 First Differences

Null Hypothesis: D(SNP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.13807	0.0000
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SNP,2)
Method: Least Squares
Date: 11/22/24 Time: 17:00
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SNP(-1))	-0.925348	0.076235	-12.13807	0.0000
C	8.536824	3.941536	2.165862	0.0317

R-squared	0.464285	Mean dependent var	0.326512
Adjusted R-squared	0.461133	S.D. dependent var	69.37420
S.E. of regression	50.92589	Akaike info criterion	10.71018
Sum squared resid	440885.9	Schwarz criterion	10.74678
Log likelihood	-919.0755	Hannan-Quinn criter.	10.72503
F-statistic	147.3327	Durbin-Watson stat	1.989362
Prob(F-statistic)	0.000000		

Unites Stated Gross Domestic Product

Null Hypothesis: GDP has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.239751	0.9296
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP)
Method: Least Squares
Date: 11/22/24 Time: 17:02
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDP(-1)	-0.001289	0.005378	-0.239751	0.8108
D(GDP(-1))	-0.252361	0.074563	-3.384561	0.0009
C	58.07192	92.04621	0.630900	0.5290

R-squared	0.064123	Mean dependent var	28.83090
Adjusted R-squared	0.053048	S.D. dependent var	88.25329
S.E. of regression	85.88057	Akaike info criterion	11.76108
Sum squared resid	1246455.	Schwarz criterion	11.81598
Log likelihood	-1008.453	Hannan-Quinn criter.	11.78335
F-statistic	5.789664	Durbin-Watson stat	1.990860
Prob(F-statistic)	0.003698		

Unites Stated Gross Domestic Product First Differences

Null Hypothesis: D(GDP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-16.86014	0.0000
Test critical values:	1% level	-3.468521	
	5% level	-2.878212	
	10% level	-2.575737	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP,2)
Method: Least Squares
Date: 11/22/24 Time: 17:03
Sample (adjusted): 2003M03 2017M06
Included observations: 172 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDP(-1))	-1.252955	0.074315	-16.86014	0.0000
C	36.06560	6.867348	5.251750	0.0000

R-squared	0.625769	Mean dependent var	0.230138
Adjusted R-squared	0.623567	S.D. dependent var	139.5867
S.E. of regression	85.64217	Akaike info criterion	11.74979
Sum squared resid	1246879.	Schwarz criterion	11.78639
Log likelihood	-1008.482	Hannan-Quinn criter.	11.76464
F-statistic	284.2644	Durbin-Watson stat	1.991563
Prob(F-statistic)	0.000000		

Consumer Price Index

Null Hypothesis: CPIAUCSL has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.362068	0.5998
Test critical values:	1% level	-3.468749	
	5% level	-2.878311	
	10% level	-2.575791	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CPIAUCSL)
Method: Least Squares
Date: 11/27/24 Time: 12:16
Sample (adjusted): 2003M04 2017M06
Included observations: 171 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CPIAUCSL(-1)	-0.003433	0.002520	-1.362068	0.1750
D(CPIAUCSL(-1))	0.564074	0.074726	7.548551	0.0000
D(CPIAUCSL(-2))	-0.244063	0.074597	-3.271753	0.0013
C	0.987229	0.552672	1.786283	0.0759

R-squared	0.265068	Mean dependent var	0.352415
Adjusted R-squared	0.251865	S.D. dependent var	0.684840
S.E. of regression	0.592351	Akaike info criterion	1.813678
Sum squared resid	58.59682	Schwarz criterion	1.887167
Log likelihood	-151.0694	Hannan-Quinn criter.	1.843496
F-statistic	20.07727	Durbin-Watson stat	2.001829
Prob(F-statistic)	0.000000		

Consumer Price Index First Differences

Null Hypothesis: D(CPIAUCSL) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.615809	0.0000
Test critical values:	1% level	-3.468749	
	5% level	-2.878311	
	10% level	-2.575791	

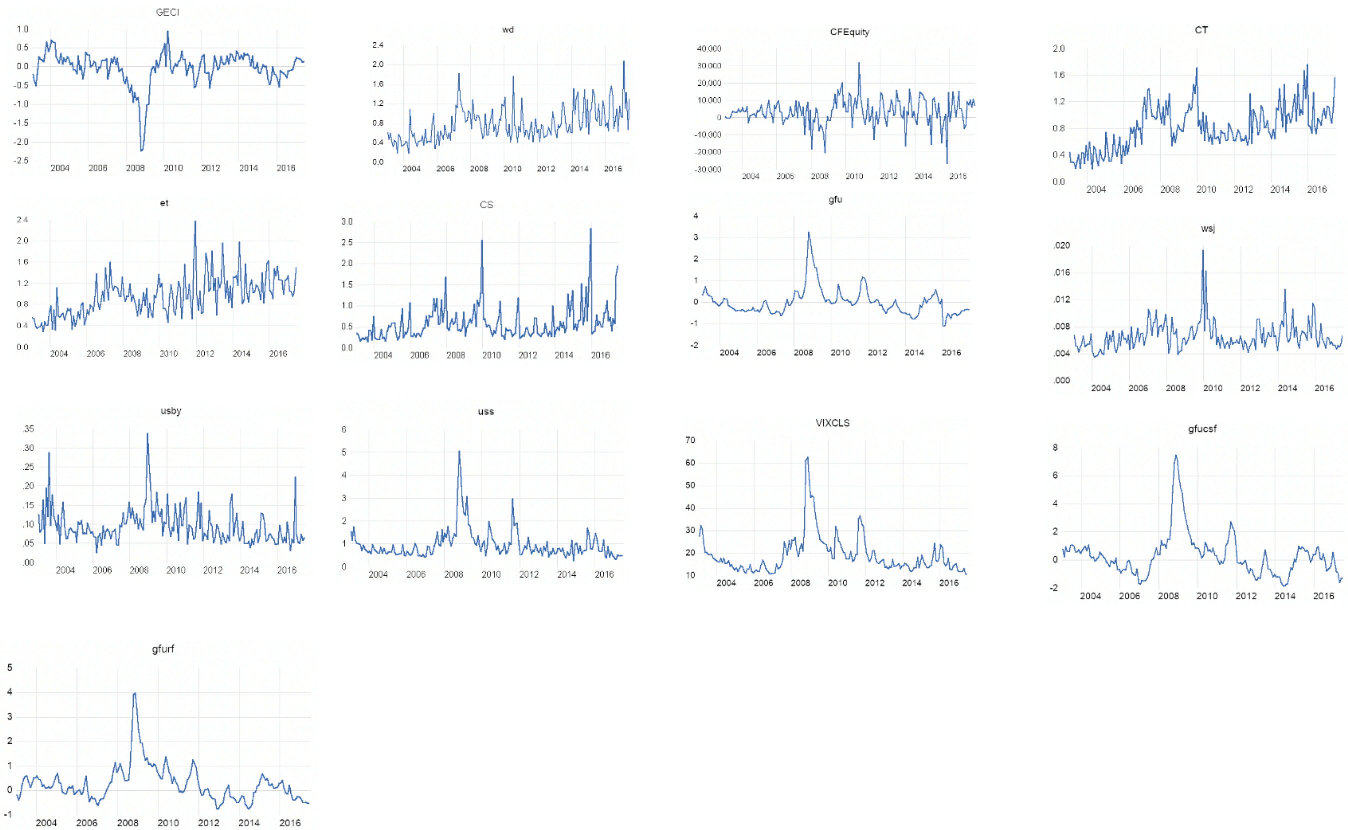
*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CPIAUCSL,2)
Method: Least Squares
Date: 11/27/24 Time: 12:16
Sample (adjusted): 2003M04 2017M06
Included observations: 171 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CPIAUCSL(-1))	-0.671173	0.077900	-8.615809	0.0000
D(CPIAUCSL(-1),2)	0.240832	0.074749	3.221877	0.0015
C	0.237935	0.053242	4.468914	0.0000

R-squared	0.312644	Mean dependent var	-0.000825
Adjusted R-squared	0.304462	S.D. dependent var	0.712067
S.E. of regression	0.593856	Akaike info criterion	1.813030
Sum squared resid	59.24778	Schwarz criterion	1.868146
Log likelihood	-152.0140	Hannan-Quinn criter.	1.835394
F-statistic	38.20748	Durbin-Watson stat	1.997796
Prob(F-statistic)	0.000000		

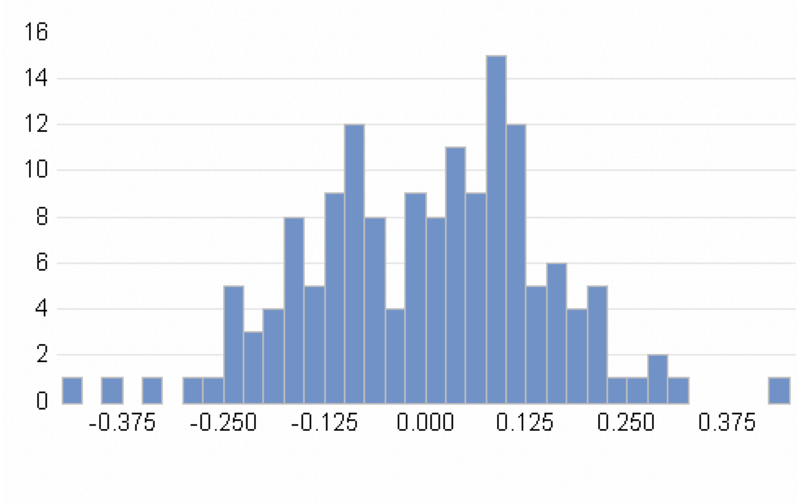
Table 14 | Graphs of independent variables



***Note*:** From left to right, Global Economic Conditions Indicator, Water & Drought, Capital Flow Equity, Carbon Tax, Extreme Temperatures, Climate Summits, Global Financial Uncertainty, Wall Street Journal index, United States Bond Yields, United States Stock, Volatility index, Global Financial Uncertainty country-specific, Global Financial Uncertianty regional factor.

Model 2 results

Table 15 | Model 2 JB Test



Series: Residuals	
Sample 2004M10 2017M06	
Observations 153	
Mean	2.15e-16
Median	0.013923
Maximum	0.437416
Minimum	-0.427887
Std. Dev.	0.145299
Skewness	-0.140664
Kurtosis	3.084192
Jarque-Bera	0.549739
Probability	0.759671

Table 16 | Model 2 OLS

Dependent Variable: D(GFC)
Method: Least Squares
Date: 11/23/24 Time: 12:38
Sample (adjusted): 2004M10 2017M06
Included observations: 153 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.159041	0.097602	-1.629488	0.1056
CPF(-3)	0.083008	0.026007	3.191740	0.0018
GECI	0.218668	0.048210	4.535735	0.0000
WD(-7)	-0.203228	0.046218	-4.397192	0.0000
WSJ(-1)	-21.13947	7.790894	-2.713356	0.0075
USEXR(-2)	-0.377618	0.112280	-3.363193	0.0010
GFU	-0.355014	0.037810	-9.389337	0.0000
CFEQUITY(-2)	-5.16E-06	1.85E-06	-2.784787	0.0061
D(DGS10(-12))	-0.198822	0.065562	-3.032577	0.0029
D(CPIAUCSL(-4))	-0.090908	0.019559	-4.647806	0.0000
ET(-4)	-0.157816	0.041434	-3.808859	0.0002
D(LOG(SNP(-7)))	-1.331251	0.335019	-3.973656	0.0001
D(GEPUCURRENT(-1))	-0.001652	0.000503	-3.282542	0.0013
USBY(-3)	1.126922	0.355113	3.173420	0.0019
LOG(USS(-11))	-0.081841	0.029566	-2.768067	0.0064
D(IPCC(-20))	0.144653	0.046825	3.089238	0.0024
VIXCLS(-1)	0.028657	0.002684	10.67588	0.0000
CT(-3)	0.122799	0.054805	2.240667	0.0267
CS(-1)	0.120561	0.041815	2.883190	0.0046
D(GDP)	0.000334	0.000159	2.101289	0.0375

R-squared	0.777752	Mean dependent var	-0.007130
Adjusted R-squared	0.746003	S.D. dependent var	0.308209
S.E. of regression	0.155332	Akaike info criterion	-0.765160
Sum squared resid	3.209010	Schwarz criterion	-0.369025
Log likelihood	78.53477	Hannan-Quinn criter.	-0.604244
F-statistic	24.49639	Durbin-Watson stat	2.291544
Prob(F-statistic)	0.000000		

Table 17 | Model 2 Correlogram

Date: 11/23/24 Time: 12:39
Sample (adjusted): 2004M10 2017M06
Q-statistic probabilities adjusted for 19 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.146	-0.146	3.3416	0.068
		2	0.046	0.025	3.6768	0.159
		3	-0.034	-0.024	3.8593	0.277
		4	0.051	0.043	4.2783	0.370
		5	0.076	0.093	5.1942	0.393
		6	-0.016	0.004	5.2355	0.514
		7	0.003	-0.002	5.2369	0.631
		8	-0.073	-0.073	6.1057	0.635
		9	-0.024	-0.057	6.2039	0.719
		10	0.046	0.034	6.5611	0.766
		11	0.080	0.097	7.6313	0.746
		12	-0.185	-0.163	13.376	0.342
		13	-0.062	-0.107	14.036	0.371
		14	-0.023	-0.032	14.125	0.440
		15	-0.034	-0.064	14.327	0.501
		16	-0.020	-0.037	14.394	0.569
		17	-0.184	-0.170	20.268	0.261
		18	-0.025	-0.071	20.378	0.312
		19	-0.052	-0.040	20.858	0.345
		20	0.030	-0.004	21.017	0.396
		21	-0.071	-0.095	21.911	0.405
		22	-0.069	-0.086	22.773	0.415
		23	-0.057	-0.056	23.363	0.440
		24	0.143	0.117	27.128	0.299
		25	0.070	0.079	28.038	0.306
		26	0.024	0.025	28.146	0.351
		27	0.093	0.123	29.769	0.325
		28	-0.004	0.054	29.772	0.374
		29	0.082	0.010	31.072	0.362
		30	-0.015	-0.067	31.115	0.410
		31	0.066	0.001	31.952	0.419
		32	-0.031	-0.020	32.139	0.460
		33	-0.022	-0.049	32.233	0.505
		34	0.012	-0.092	32.261	0.553
		35	0.042	-0.050	32.610	0.584
		36	0.039	0.041	32.923	0.616

*Probabilities may not be valid for this equation specification.

Table 18 | Model 2 Correlogram of squared residuals

Date: 11/23/24 Time: 12:39
Sample (adjusted): 2004M10 2017M06
Included observations: 153 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.024	0.024	0.0878	0.767
		2	-0.133	-0.134	2.8710	0.238
		3	0.098	0.107	4.3875	0.223
		4	-0.128	-0.157	6.9974	0.136
		5	-0.069	-0.029	7.7543	0.170
		6	0.081	0.036	8.8170	0.184
		7	-0.076	-0.072	9.7616	0.202
		8	0.003	0.020	9.7627	0.282
		9	0.060	0.012	10.353	0.323
		10	-0.123	-0.102	12.868	0.231
		11	-0.001	0.007	12.868	0.302
		12	0.021	-0.029	12.944	0.373
		13	-0.000	0.043	12.944	0.452
		14	-0.018	-0.056	12.998	0.527
		15	0.001	-0.004	12.998	0.602
		16	-0.123	-0.129	15.626	0.479
		17	-0.106	-0.109	17.584	0.416
		18	0.022	-0.009	17.666	0.478
		19	0.024	0.011	17.764	0.538
		20	0.015	-0.005	17.805	0.600
		21	0.045	0.005	18.170	0.638
		22	-0.007	-0.019	18.177	0.695
		23	-0.037	-0.026	18.429	0.734
		24	0.076	0.057	19.484	0.726
		25	0.000	0.002	19.484	0.773
		26	-0.000	0.006	19.484	0.815
		27	0.024	-0.022	19.597	0.847
		28	0.085	0.110	20.968	0.827
		29	0.022	0.030	21.063	0.857
		30	0.005	0.021	21.067	0.886
		31	-0.006	-0.008	21.075	0.910
		32	-0.020	-0.016	21.156	0.928
		33	-0.019	-0.040	21.227	0.943
		34	-0.041	-0.042	21.564	0.952
		35	-0.019	-0.005	21.636	0.962
		36	-0.070	-0.077	22.634	0.960

Table 19 | Model 2 Breusch Pagan Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	1.456778	Prob. F(19,133)	0.1117
Obs*R-squared	26.35602	Prob. Chi-Square(19)	0.1206
Scaled explained SS	20.75429	Prob. Chi-Square(19)	0.3505

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 11/23/24 Time: 12:38
Sample: 2004M10 2017M06
Included observations: 153

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.004786	0.018566	-0.257811	0.7970
CPF(-3)	0.004923	0.004947	0.995155	0.3215
GECI	-0.015627	0.009171	-1.704004	0.0907
WD(-7)	-0.004438	0.008792	-0.504830	0.6145
WSJ(-1)	1.349381	1.481981	0.910525	0.3642
USEXR(-2)	0.015175	0.021358	0.710503	0.4786
GFU	-0.008875	0.007192	-1.234013	0.2194
CFEQUITY(-2)	-3.74E-07	3.53E-07	-1.061693	0.2903
D(DGS10(-12))	-0.007057	0.012471	-0.565884	0.5724
D(CPIAUCSL(-4))	-0.004574	0.003721	-1.229473	0.2211
ET(-4)	-0.001728	0.007882	-0.219196	0.8268
D(LOG(SNP(-7)))	0.033492	0.063727	0.525557	0.6001
D(GEPUCURRENT(-1))	8.88E-05	9.57E-05	0.928005	0.3551
USBY(-3)	-0.019984	0.067549	-0.295849	0.7678
LOG(USS(-11))	0.002976	0.005624	0.529141	0.5976
D(IPCC(-20))	-0.005616	0.008907	-0.630557	0.5294
VIXCLS(-1)	0.000163	0.000511	0.319357	0.7500
CT(-3)	0.006089	0.010425	0.584045	0.5602
CS(-1)	0.015280	0.007954	1.921086	0.0569
D(GDP)	4.10E-05	3.03E-05	1.355434	0.1776

R-squared	0.172262	Mean dependent var	0.020974
Adjusted R-squared	0.054013	S.D. dependent var	0.030379
S.E. of regression	0.029547	Akaike info criterion	-4.084313
Sum squared resid	0.116113	Schwarz criterion	-3.688177
Log likelihood	332.4499	Hannan-Quinn criter.	-3.923396
F-statistic	1.456778	Durbin-Watson stat	1.964001
Prob(F-statistic)	0.111677		

Table 20 | Model 2 VIF Test

Variance Inflation Factors
Date: 11/23/24 Time: 12:43
Sample: 2003M01 2017M06
Included observations: 153

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.009526	60.40703	NA
CPF(-3)	0.000676	1.337141	1.332767
GECI	0.002324	2.994442	2.912688
WD(-7)	0.002136	9.949025	1.358160
WSJ(-1)	60.69803	19.77923	1.694292
USEXR(-2)	0.012607	17.55515	2.345970
GFU	0.001430	3.888009	3.887969
CFEQUITY(-2)	3.44E-12	1.625571	1.385094
D(DGS10(-12))	0.004298	1.203165	1.195110
D(CPIAUCSL(-4))	0.000383	1.535375	1.212631
ET(-4)	0.001717	12.12632	1.294663
D(LOG(SNP(-7)))	0.112238	1.185041	1.172094
D(GEPUCURRENT(-1))	2.53E-07	1.127836	1.127193
USBY(-3)	0.126105	8.214455	1.511682
LOG(USS(-11))	0.000874	1.529199	1.383691
D(IPCC(-20))	0.002193	1.209618	1.209467
VIXCLS(-1)	7.21E-06	20.12176	3.626965
CT(-3)	0.003004	15.38081	1.656323
CS(-1)	0.001749	5.951365	1.746151
D(GDP)	2.53E-08	1.390648	1.276851

Table 21 | Model 2 Model's stationarity

Null Hypothesis: RESID02 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.19817	0.0000
Test critical values:	1% level	-3.473672	
	5% level	-2.880463	
	10% level	-2.576939	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESID02)
Method: Least Squares
Date: 11/23/24 Time: 12:44
Sample (adjusted): 2004M11 2017M06
Included observations: 152 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID02(-1)	-1.146380	0.080741	-14.19817	0.0000
C	-0.000332	0.011730	-0.028298	0.9775

R-squared	0.573364	Mean dependent var	-0.000537
Adjusted R-squared	0.570520	S.D. dependent var	0.220678
S.E. of regression	0.144621	Akaike info criterion	-1.016330
Sum squared resid	3.137283	Schwarz criterion	-0.976542
Log likelihood	79.24111	Hannan-Quinn criter.	-1.000167
F-statistic	201.5881	Durbin-Watson stat	1.993383
Prob(F-statistic)	0.000000		

Table 22 | Model 2 Forecast graph

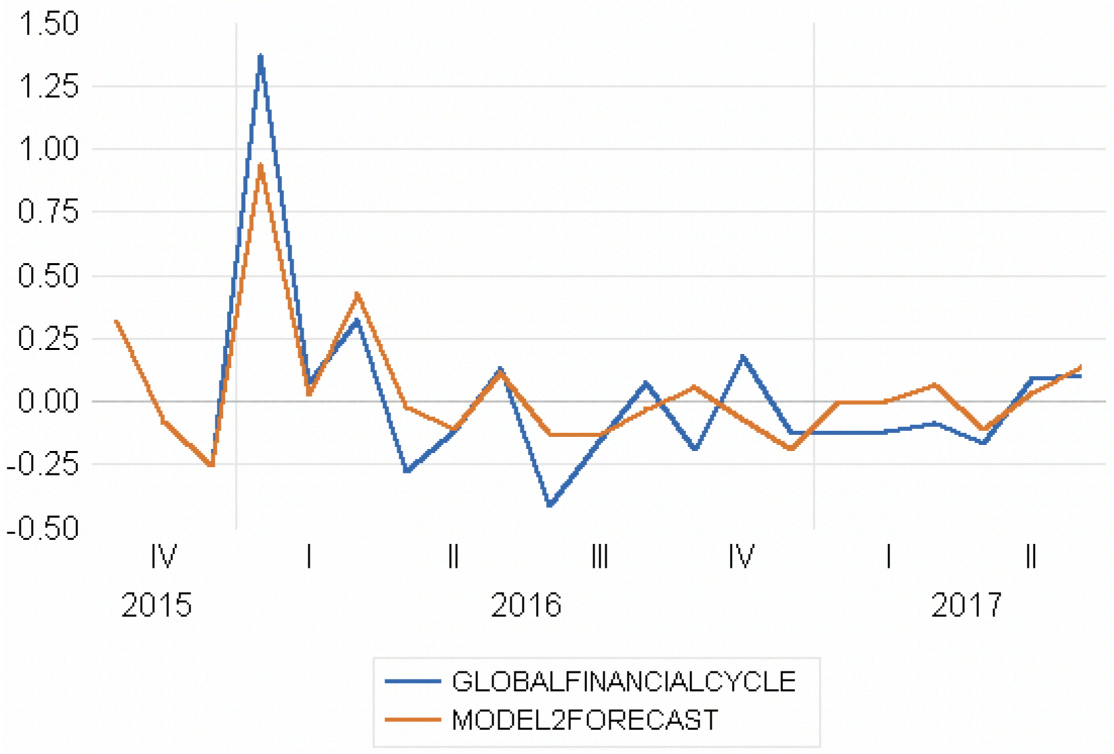


Table 23 | Model 2 Actual, Fitted Residual Graph

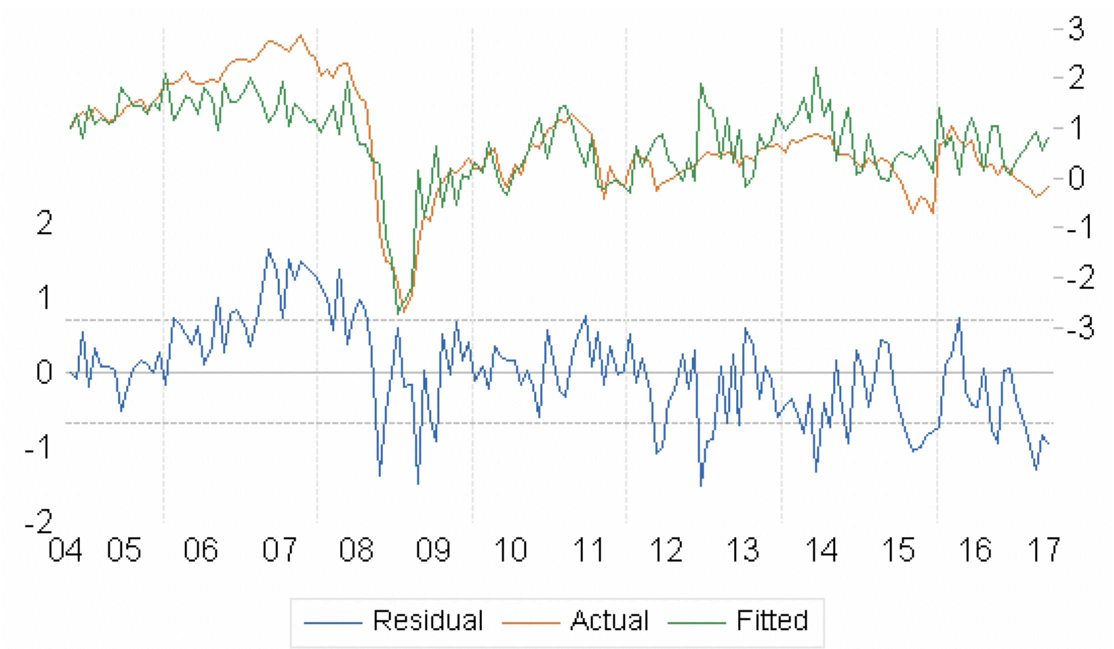
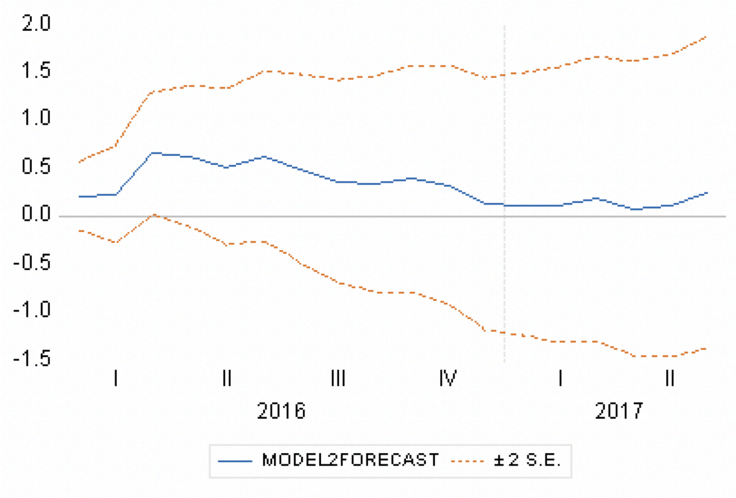
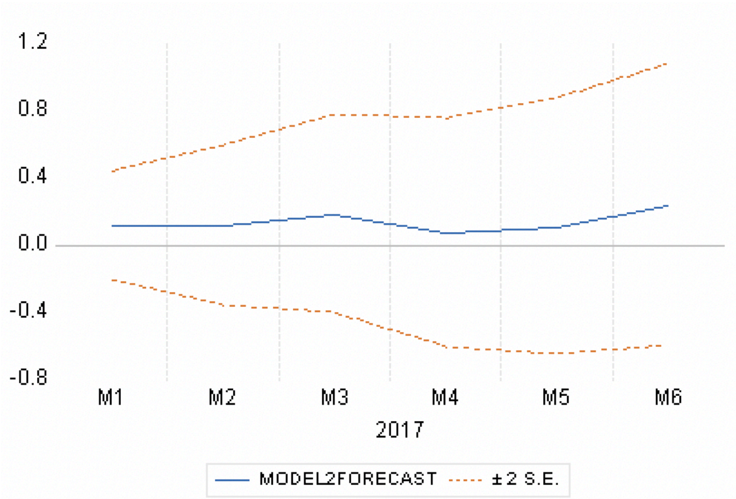


Table 24 | Model 2 Forecast first period GFCy



Forecast: MODEL2FORECAST	
Actual: GFC	
Forecast sample: 2016M01 2017M06	
Included observations: 18	
Root Mean Squared Error	0.296086
Mean Absolute Error	0.252806
Mean Abs. Percent Error	245.3766
Theil Inequality Coef.	0.344961
Bias Proportion	0.048173
Variance Proportion	0.556755
Covariance Proportion	0.395072
Theil U2 Coefficient	2.037225
Symmetric MAPE	100.1272

Table 25 | Model 2 Forecast second period GFCy



Forecast: MODEL2FORECAST	
Actual: GFC	
Forecast sample: 2017M01 2017M06	
Included observations: 6	
Root Mean Squared Error	0.356827
Mean Absolute Error	0.336885
Mean Abs. Percent Error	568.7093
Theil Inequality Coef.	0.938635
Bias Proportion	0.891350
Variance Proportion	0.031928
Covariance Proportion	0.076723
Theil U2 Coefficient	2.004720
Symmetric MAPE	200.0000

Model 3 Results

Table 26 | Model 2 ARMA results

Dependent Variable: D(GFC)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/26/24 Time: 13:09
Sample: 2004M10 2017M06
Included observations: 153
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.180874	0.087914	-2.057400	0.0416
CPF(-3)	0.092731	0.024516	3.782523	0.0002
GECI	0.232023	0.044026	5.270141	0.0000
WD(-7)	-0.168886	0.046470	-3.634300	0.0004
WSJ(-1)	-12.93769	5.528477	-2.340190	0.0208
USEXR(-2)	-0.335813	0.112562	-2.983350	0.0034
GFU	-0.354274	0.034727	-10.20156	0.0000
CFEQUITY(-2)	-7.18E-06	1.97E-06	-3.650285	0.0004
D(DGS10(-12))	-0.206380	0.071255	-2.896366	0.0044
D(CPIAUCSL(-4))	-0.092866	0.016888	-5.499045	0.0000
ET(-4)	-0.158616	0.039761	-3.989196	0.0001
D(LOG(SNP(-7)))	-1.464895	0.343757	-4.261421	0.0000
D(GEPUCURRENT(-1))	-0.001485	0.000525	-2.829406	0.0054
USBY(-3)	1.243615	0.317981	3.910973	0.0001
LOG(USS(-11))	-0.057636	0.025706	-2.242122	0.0266
D(IPCC(-20))	0.215955	0.053316	4.050468	0.0001
VIXCLS(-1)	0.027089	0.002693	10.06054	0.0000
CT(-3)	0.148344	0.054193	2.737338	0.0071
D(GDP)	0.000521	0.000179	2.914703	0.0042
AR(12)	-0.308276	0.100964	-3.053319	0.0027
MA(1)	-0.191145	0.095440	-2.002771	0.0473
SIGMASQ	0.020225	0.002868	7.051174	0.0000

R-squared	0.785692	Mean dependent var	-0.007130
Adjusted R-squared	0.751337	S.D. dependent var	0.308209
S.E. of regression	0.153692	Akaike info criterion	-0.767319
Sum squared resid	3.094371	Schwarz criterion	-0.331570
Log likelihood	80.69991	Hannan-Quinn criter.	-0.590311
F-statistic	22.86998	Durbin-Watson stat	1.999191
Prob(F-statistic)	0.000000		

Inverted AR Roots	.88-.23i	.88+.23i	.64-.64i	.64+.64i
	.23-.88i	.23+.88i	-.23+.88i	-.23-.88i
	-.64-.64i	-.64-.64i	-.88+.23i	-.88-.23i
Inverted MA Roots	.19			

Table 27 | Model 3Correlogram

Date: 11/26/24 Time: 13:10
Sample (adjusted): 2004M10 2017M06
Q-statistic probabilities adjusted for 2 ARMA terms and 18 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.002	-0.002	0.0004	
		2	0.009	0.009	0.0134	
		3	-0.027	-0.027	0.1313	0.717
		4	0.026	0.026	0.2385	0.888
		5	0.030	0.030	0.3786	0.945
		6	-0.019	-0.020	0.4375	0.979
		7	0.068	0.069	1.1956	0.945
		8	-0.051	-0.050	1.6269	0.951
		9	0.002	-0.002	1.6275	0.978
		10	0.034	0.040	1.8239	0.986
		11	-0.026	-0.032	1.9377	0.992
		12	-0.004	-0.006	1.9403	0.997
		13	-0.062	-0.054	2.5943	0.995
		14	-0.039	-0.050	2.8552	0.996
		15	-0.046	-0.038	3.2117	0.997
		16	-0.029	-0.031	3.3536	0.998
		17	-0.147	-0.155	7.1386	0.954
		18	-0.089	-0.083	8.5381	0.931
		19	-0.093	-0.102	10.080	0.900
		20	0.009	0.001	10.094	0.929
		21	-0.122	-0.129	12.786	0.849
		22	-0.099	-0.112	14.576	0.800
		23	-0.095	-0.111	16.207	0.758
		24	0.051	0.046	16.693	0.780
		25	0.071	0.057	17.640	0.777
		26	0.105	0.119	19.718	0.713
		27	0.090	0.110	21.232	0.680
		28	-0.030	0.001	21.406	0.721
		29	0.029	0.043	21.565	0.759
		30	0.010	0.003	21.585	0.800
		31	-0.006	-0.040	21.593	0.837
		32	-0.049	-0.091	22.068	0.852
		33	0.020	-0.022	22.148	0.878
		34	-0.015	-0.106	22.194	0.902
		35	0.071	0.010	23.211	0.897
		36	0.066	-0.021	24.104	0.896

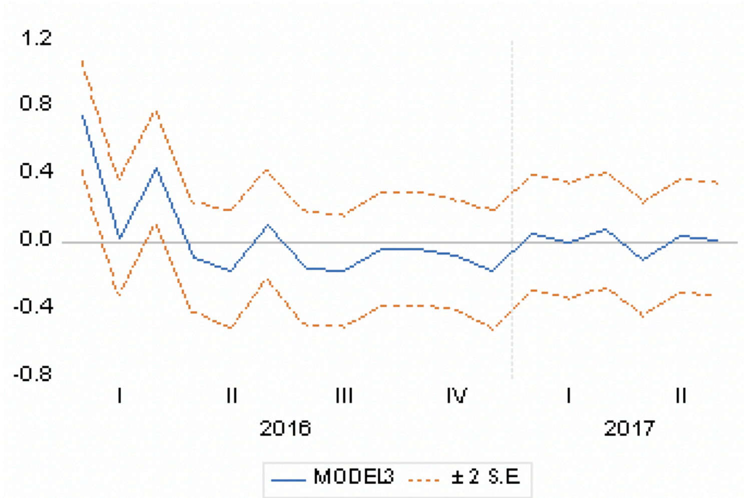
*Probabilities may not be valid for this equation specification.

Table 28 | Model 3Correlogram of residuals squared

Date: 11/26/24 Time: 13:10
Sample (adjusted): 2004M10 2017M06
Included observations: 153 after adjustments

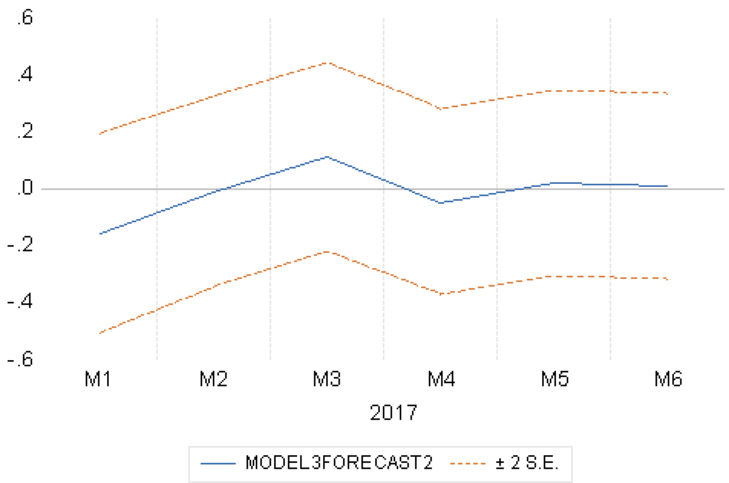
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.029	-0.029	0.1283	0.720
		2	-0.084	-0.085	1.2407	0.538
		3	0.119	0.115	3.4702	0.325
		4	-0.020	-0.021	3.5328	0.473
		5	-0.006	0.012	3.5393	0.617
		6	0.071	0.055	4.3511	0.629
		7	-0.048	-0.042	4.7315	0.693
		8	-0.073	-0.067	5.6046	0.691
		9	0.009	-0.015	5.6188	0.777
		10	-0.018	-0.017	5.6707	0.842
		11	-0.008	0.005	5.6812	0.894
		12	-0.085	-0.095	6.8827	0.865
		13	-0.036	-0.031	7.1000	0.897
		14	0.027	0.018	7.2208	0.926
		15	0.013	0.024	7.2511	0.950
		16	-0.088	-0.086	8.6021	0.929
		17	-0.005	-0.014	8.6071	0.952
		18	0.032	0.025	8.7919	0.964
		19	-0.027	-0.013	8.9249	0.975
		20	0.050	0.035	9.3674	0.978
		21	0.067	0.058	10.176	0.977
		22	0.028	0.057	10.315	0.983
		23	-0.022	-0.028	10.406	0.988
		24	0.157	0.134	14.951	0.922
		25	-0.059	-0.069	15.586	0.927
		26	-0.044	-0.020	15.940	0.938
		27	0.039	-0.008	16.231	0.948
		28	0.035	0.046	16.459	0.959
		29	-0.048	-0.038	16.890	0.964
		30	-0.044	-0.051	17.258	0.969
		31	-0.042	-0.041	17.600	0.974
		32	-0.035	-0.016	17.838	0.979
		33	-0.022	-0.027	17.931	0.985
		34	-0.039	-0.030	18.233	0.988
		35	0.002	0.002	18.233	0.991
		36	-0.035	-0.003	18.480	0.993

Table 29 | Model 3 Forecast first period



Forecast: MODEL3	
Actual: D(GFC)	
Forecast sample: 2016M01 2017M06	
Included observations: 18	
Root Mean Squared Error	0.197255
Mean Absolute Error	0.142023
Mean Abs. Percent Error	75.71718
Theil Inequality Coef.	0.330332
Bias Proportion	0.000269
Variance Proportion	0.529558
Covariance Proportion	0.470173
Theil U2 Coefficient	0.568275
Symmetric MAPE	103.6912

Table 32 | Model 3 Forecast second period



Forecast: MODEL3FORECAST2	
Actual: D(GFC)	
Forecast sample: 2017M01 2017M06	
Included observations: 6	
Root Mean Squared Error	0.117210
Mean Absolute Error	0.104456
Mean Abs. Percent Error	96.48729
Theil Inequality Coef.	0.585782
Bias Proportion	0.112420
Variance Proportion	0.054864
Covariance Proportion	0.832716
Theil U2 Coefficient	1.457813
Symmetric MAPE	133.6415

Table 31 | Model 3 Forecast graph

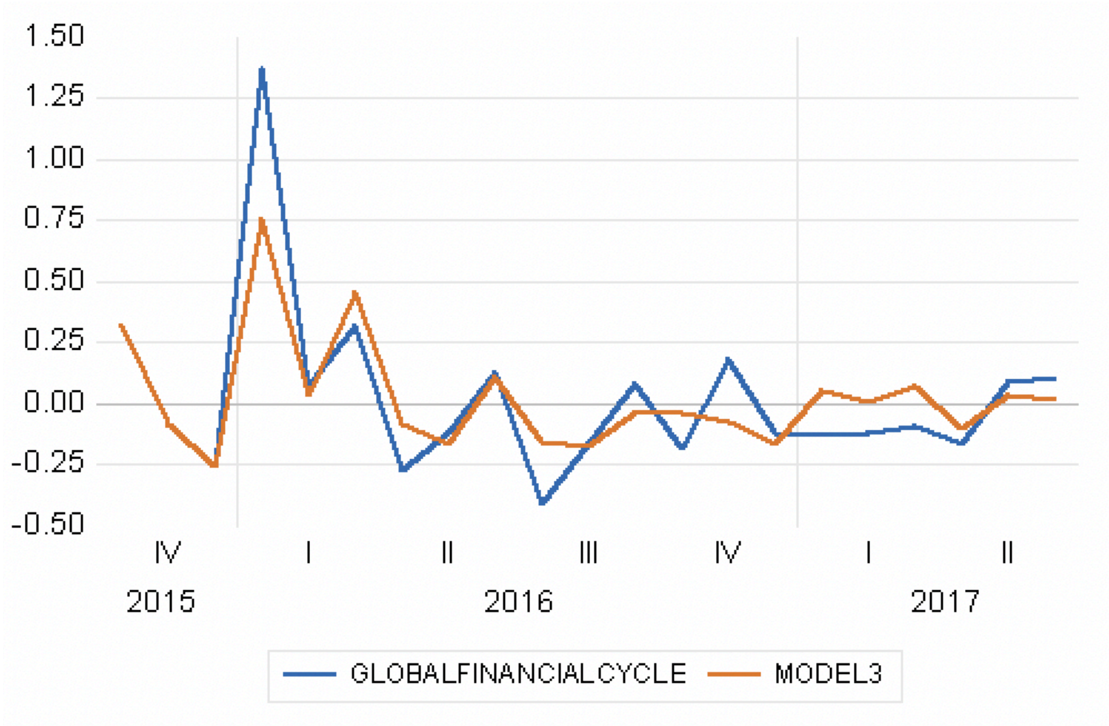


Table 32 | Model 3 Actual, Fitted Residual Graph

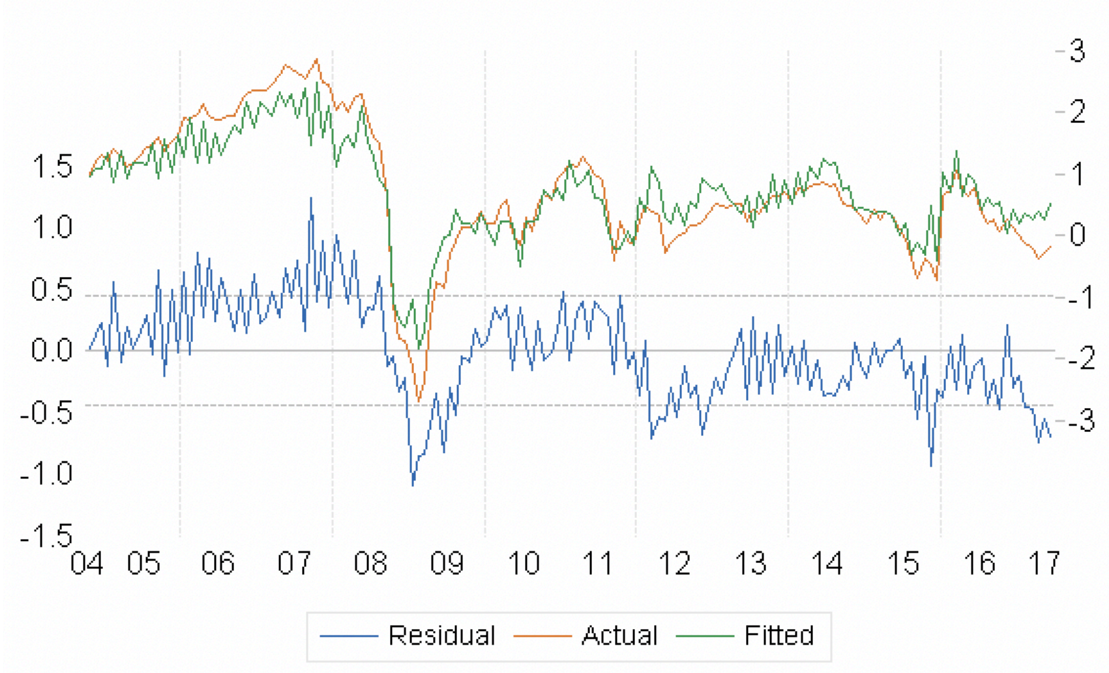


Table 33 | Model 3 forecast first period GFCy

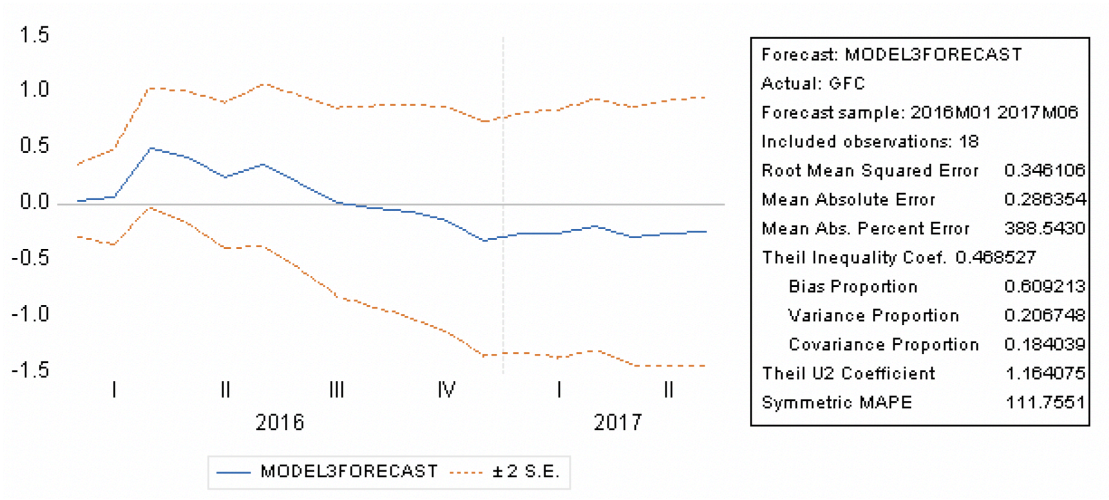


Table 34 | Model 3 forecast second period GFCy