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Why Climate Change should be considered within Financial Programming framework?

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Hereby I declare that this master thesis, my original investigation and achievement, submitted for the master's degree at ADA University has not been submitted for any degree or examination.

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List of abbreviations

ADF	Augmented Dickey-Fuller test
AIC	Akaike Info Criterion
ARDL	Autoregressive Distributed Lag
BP	British Petroleum
ECB	European Central Bank
EME	Emerging Market Economies
FP	Financial Programming
GDP	Gross Domestic Product
IMF	International Monetary Fund
KPSS	Kwiatkowski-Phillips-Schmidt-Shin test
SIC	Schwarz Info Criterion

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Abstract

This research aims to improve the IMF's Financial Programming framework by inserting the climate change factor into the analysis, neglecting the vital relationship between global warming and the IMF's accuracy in GDP predictions. Under the climate change variable, the study tracks carbon dioxide emissions on both global and separately national scales. The study employs ARDL as a basis for the empirical research methodology and uses four distinctive models with CO_2 emissions and FP's two (1)/ six (2)-year global (3)/ panel (4) GDP forecasting accuracies. Global and panel GDP forecast accuracy deviation of the countries for six years is out of investigation due to the small sample size. The findings of the time series show that by keeping all other variables stable, a 1% increase in the first lagged global GDP forecast accuracy deviation for two years deteriorates the named forecast accuracy (increases GDP forecast accuracy deviation for two years) in the short run by 0.624%, on average. The findings of the panel data, on the other hand, dictate that, ceteris paribus, a 1% increase in carbon dioxide emissions decreases the two-year GDP forecast accuracy deviation of paneled countries by only 0.66%, on average. Thus, albeit of statistical essence, neither in the short term nor in the long, the CO_2 emissions significantly affect the FP's global two-year GDP forecasting accuracy in economic terms.

Keywords: Financial programming, Macroeconomic diagnostics, Forecast accuracy, Climate Change, Carbon dioxide emissions, ARDL

Introduction

"Financial and monetary policy tools can help with Climate Change Mitigation efforts."

William Oman
Insights & Analysis on Economics & Finance, 2019

Financial Programming [hereinafter FP] is a well-known quantitative framework designed by the International Monetary Fund that assists countries to achieve desired macroeconomic objectives and links them to policy measures (IMF Institute, 2014). Current account improvement, stable and low inflation rate, high growth rate are the typical and most essential FP objectives. Based on these determining and ultimate objectives, under international standards set by the IMF, central banks conduct policy analysis and imply respective measures. The framework was designed in 1956 and initially introduced as an analytical tool to tie monetary analysis and payment problems (Polak, 1957). Since the framework encompasses real, fiscal, external, monetary & financial sector analysis contemplated by the central banks, FP is utilitarian and valuable in the context of the monetary policy management as well as conducting monetary policy and imply respective measures. Countries work in cooperation with the IMF and set IMF-supported policy targets and elicit self-related variations of universal FP methodology; The FP methodology is so important and vital that most countries in Africa are even dependent on the universal methodology for the technical analysis (Bolnick, 1999).

However, to say that FP does not have limitations would be far from what the empirical analysis reveals. As a matter of fact, existing studies have found out that the said framework has circumstance-based restrictions, thereby subjecting FP to sundry examinations. All framework applications in various country cases are subject to consistency checks (Mikkelsen, 1998; Kiptoo, 2006), diverse accounting and behavioral adjustments (Rajcoomar & Bell, 1996; Barth & Hemphill, 2000), test quality and accuracy, focus on medium- and long-term implications (Mikkelsen, 1998). Some authors have gone even further to argue that the methodology does not fare well when it comes to forecasting. For instance, research done by Easterly et al. (2006) has demonstrated that the framework is not practical enough with forecasting variables and has a pitfall of "reasonable" parameters for behavioral relationships. Taking all of these studies into account compels fairness to argue that there are significant deficiencies of the FP tools, which renders the whole methodology subject to errors and inaccuracies.

Another critical deficiency of the FP methodology is that it does not account for the climate change factor, a critical factor that is gradually making its way into general economic policymaking, including monetary policy. Since climate change is a missing factor in the FP methodology, this research aims to improve the FP tools and the framework by inserting the climate change factor into the analysis. The climate change factor is an essential and – reasonable parameter in this regard because it influences the soundness of the framework by affecting the quality of forecasting and supplementary policy measures. Even the most heterodox FP-suggested policy measures lack the "climate change factor" inclusiveness. What is even more remarkable is that economic agencies barely consider the deteriorating externalities of climate change neither in assessing and projecting ongoing conditions and circumstances nor in making forecasts about the short-term and long-term future. Inclusion of the climate change factor into the FP methodology will further the accuracy and the utility of the said framework now that more and more central banks are factoring in climate change in how they conduct monetary policy. To that end, the research has taken a multi-pronged approach, firstly starting with the analysis of FP processing steps, moving on to identifying affected phases, and addressing the existing literature on how and in which terms global warming affects the separate variables. Regardless of the country, the standard FP process consists of the aforementioned steps (IMF Institute, 2014):

1. Macroeconomic outlook projection with existing policies;
2. Baseline scenario formulation;
3. Problem identification;
4. Setting policy objectives;
5. Policy measures identification;
6. Adjusted scenario formulation;
7. Consistency construction and decision-making.

The climate change factor is a critical element to consider in all of the above-mentioned steps. However, this thesis suggests that the effects of global warming have to be taken into account, particularly in the formulation of the baseline scenarios and identification of respective policy measures. Moving from this premise, the research objective, hereby, is to identify whether there is a relationship between the absolute deviations of FP forecasted values and climate change. In the case of a strong correlation, the thesis implies further amendments to the monetary policy measures. Under the climate change variable, the study tracks CO_2 emissions on both global and separately national scales. Fortunately, the existing literature is rich in providing the data on CO_2 emissions in IMF member states for decades and the materials required for accuracy statements.

At this moment, the research question is how the CO_2 emissions affect the FP's GDP forecasting accuracy. In order to assist better exploring the topic and answer the central research question, the thesis also aims to answer the following auxiliary research questions:

a. how the CO_2 emissions affect the FP's two-year global GDP forecasting accuracy;
b. how the CO_2 emissions affect the FP's six-year global GDP forecasting accuracy;
c. how the CO_2 emissions affect the FP's two-year multilateral GDP forecasting accuracy;
d. how the CO_2 emissions affect the FP's six-year multilateral GDP forecasting accuracy.

Hence, the research hypothesis is that the level of emissions hurts FP's GDP forecast accuracy both in separate states and on a global scale. For multilateral analysis, thesis accounts the data of 62 states available for two-year testing (provided by all databases), which is further reduced to 47 states for six-year testing [according to the statistical significance] after the consolidation processes. The precise list of countries is mentioned in the table 1. In case the premise of hurting accuracy holds, and the detrimental effect of climate change on GDP forecasting accuracy through FP is proven, climate change, represented by CO_2 emissions, should be considered for Financial Programming. Although the existing studies call upon central banks to consider environmental concerns in monetary policy toolkits (Economides & Xepapadeas, 2018; Honohan, 2019; Batten et al., 2020), the dearth of reference to climate change in the FP methodology is problematic. Many countries, faced with colossal climate change problems, are dependent on this methodology; the fact that the FP tools do not account for climate change lessens its effectiveness and utility for those countries. In the absence of such a critical factor in the FP methodology, this paper, therefore, is expected to introduce the sound novelty to the literature and recall the IMF to assert respective considerations. By this introduction, the thesis plays an original role in the sphere, neglecting the nexus between global warming and IMF's accuracy in predictions. For modeling purposes, the research employs the dynamic econometric model - autoregressive distributed lag (ARDL).

States available for two-year testing			**States available for six-year testing**		
Algeria	Hong Kong	Peru	Algeria	India	Thailand
Argentina	Hungary	Philippines	Argentina	Iran	Turkey
Australia	Iceland	Poland	Australia	Ireland	UK
Austria	India	Portugal	Austria	Israel	USA
Azerbaijan	Indonesia	Romania	Azerbaijan	Japan	Uzbekistan
Bangladesh	Iran	Russia	Belarus	Kazakhstan	
Belarus	Ireland	Saudi Arabia	Belgium	Kuwait	
Belgium	Israel	Singapore	Brazil	Latvia	
Brazil	Italy	South Korea	Bulgaria	Lithuania	
Bulgaria	Japan	Spain	Canada	Morocco	
Canada	Kazakhstan	Sweden	Chile	Netherlands	
Chile	Kuwait	Switzerland	Colombia	New Zealand	
China	Latvia	Taiwan	Denmark	Peru	
Colombia	Lithuania	Thailand	Ecuador	Poland	
Denmark	Luxembourg	Turkey	Estonia	Portugal	
Ecuador	Malaysia	UK	Finland	Romania	
Estonia	Mexico	USA	France	Russia	
Finland	Morocco	Uzbekistan	Germany	South Korea	
France	Netherlands	Venezuela	Greece	Sweden	
Germany	New Zealand	Vietnam	Hong Kong	Switzerland	
Greece	Norway		Hungary	Taiwan	

Table 1. The list of countries included in analysis

Literature review

Existing studies shed light on the strong influence of climate change on monetary policy conduct by illustrating the relationship between macroeconomic and financial factors (IMF, 2019a). Along with its impacts on the key macroeconomic factors like output, consumption, investment, total productivity, employment, wages, exchange rates, actual and expected inflations, which are determining characters and vital elements in the FP framework, environmental issues stand to threaten the monetary policy transmission channels as well. (Batten et al., 2020; NGFS, 2020). Figure 1 cogently demonstrates how the climate-related shocks within and outside the control of the central bank influence the transmission mechanism. Hereby, crucial factors for a monetary policy such as expectations, credits, asset prices, exchange and commercialized interest rates, and overall prices elicited from wages and import prices are all directly affected and seek a remedy to be neutralized.

What is even more noteworthy is that the literature is rich in terms of assessing the essence of an "unprecedented transition to a low-carbon economy" (Oman, 2019) but scarce for proposing ecological policy measures in regard (Krogstrup and Oman, 2019). Over the course of the last decade, many central banks around the world have tried to factor in climate change in how they set and conduct monetary policy. For instance, the Bank of England has identified climate change as one of the most critical factors in determining long-term monetary policy. On the other hand, Central banks are challenged to address the concerns by imposing new heterodox monetary policy tools to combat the spike in named concentration levels. Ament (2020) argues that the theory of money refers to the only traditional conception and has no practical application for environmental economics, which presupposes novelties in monetary policy. To facilitate the inclusion of climate change and suggested amendments to monetary policy, in particular the FP framework, thesis analyzes the impact of CO_2 on the GDP forecast accuracy. Unmitigated climate change is a severe threat: IMF (2019b) predicts that in a nine-decade period, global warming will damage EME GDP by 9 percent, while for Burke et al. (2015), similar conjunction for the plummet in global GDP is around 23 percent.

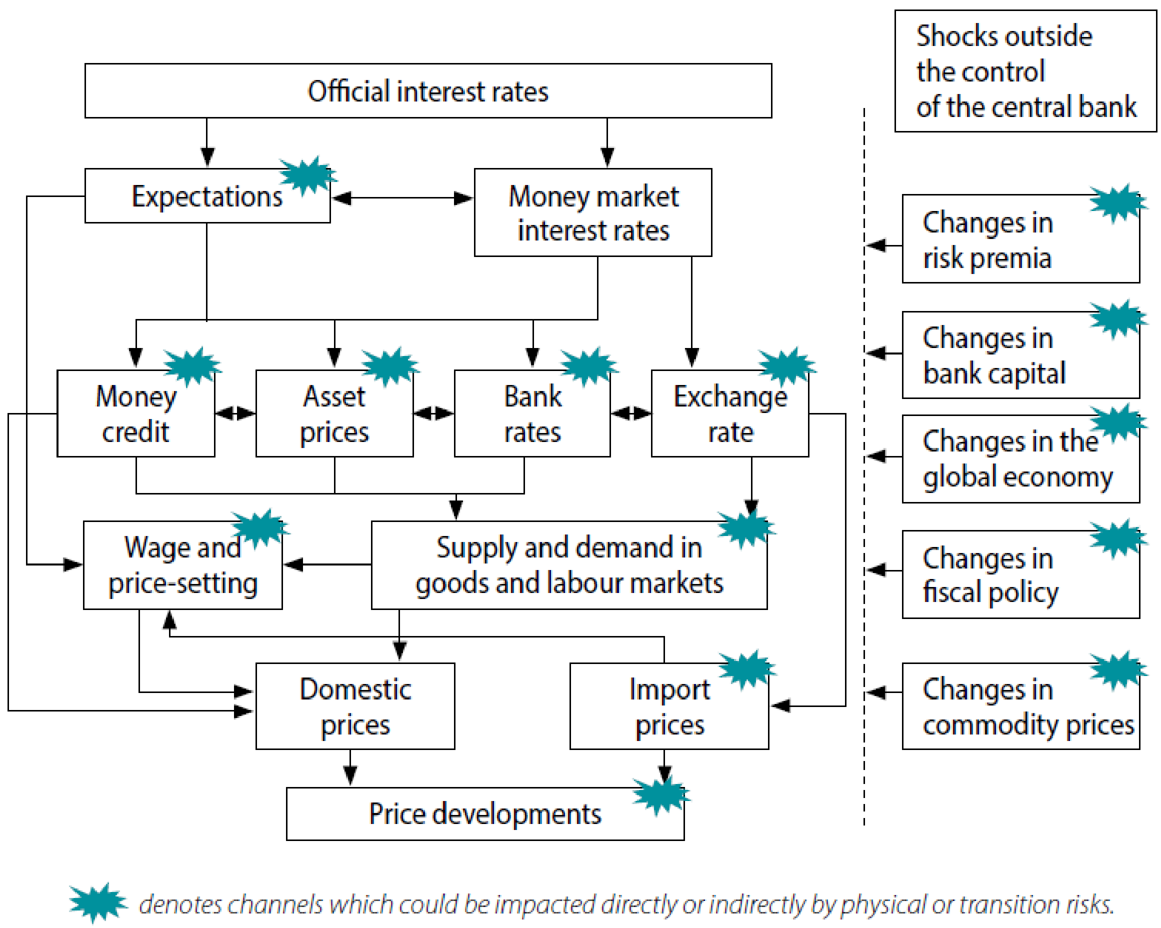

Figure 1. Impact of climate change on monetary policy transmission channels

Source: *NGFS, technical document*

Fortunately, there are certain studies on how climate change explicitly impacts GDP growth and the economy in general. One of the studies performed in 2008 (Dafermos et al.)

highlights that the climate seriously damages the financial asset prices and the depository & non-depository corporations' financial positions by reducing profitability, deteriorating financial liquidity, and obstructing credit expansion. These changes pave the way for financial instability, which has become one of the most essential and top priority tasks for the central bank worldwide in the background of the increased importance of macro-prudential policies following the 2008 Financial Crisis. The said study employed the stock-flow-fund ecological macroeconomic model. It denotes CO_2 emission as a pertinent factor in climate change, following Nordhaus and Sztorc's (2013) example, who analyzed these emissions as lead factors to the hype in atmospheric CO_2 concentration. The trend of variations in CO_2 emissions also elicits the range GDP variations according to the investment required to cover the risks (Bowen et al. 2013), or carbon-pricing, underlying its essence for considerations of forecasting tools.

Howbeit Campiglio (2016) argues that mere carbon pricing may not be sufficient for filling low-carbon investment gaps due to market failures in the process of credit expansion. In particular, he suggests amendments to EMEs' monetary policies in terms of lending strategies. Low-carbon sectors will be positively differentiated; this would lead to the variation of the credit creation multiplier, further strengthening the commercial banks' standpoints for green investment. He considers the implementation by modifying reserve requirement differentiation. This proposition may advantageously work for FP tools as well, where cogent suchlike distinction may lead to both increases in forecast quality and climate change mitigation.

In a similar line of argument, Ament (2020), Fontana and Sawyer (2015) criticized modern monetary economics and argued that the laggardness of the central banks had undermined efforts to mitigate contemporary environmental concerns. They argued on the coopted natural growth rates overseeing ecological issues, which directly concerns the FP tools inasmuch as natural growth rates stand in the heart of the framework. Investigations of Cahen-Fourota and Lavoie in 2016 intersect with Ament, Fontana, and Sawyer's research on the underdevelopment of cointegration of monetary economics with the environment. They present the interest-bearing debt system counted in stationary economics stuck in the past and reinvest in the post-Keynesian economics. The employed simple Cambridgian– Kaleckian model in the study concluded that money–growth nexus is open for applications, further proving the work on growth rates in climate change.

Taking all the estimations mentioned above into account, Chen and Pan in 2020 strived to find an optimal mix of monetary policy and environmental challenge fight. Researchers found out that climate policies may influence achieving monetary policy targets with the help of the built Environmental Dynamic Stochastic General Equilibrium model. Moreover, they adjusted the Taylor rule indicating the possibility of successful primary core formula amendments in modern monetary policy tools. They showed that welfare would be achieved if climate change would be accounted for as a monetary policy target and thereby regulated by central banks. The work by Chen and Pan indicates how much climate change is vital for GDP growth, facilitated by conducive decisions on monetary policy tools. Financial programming, if central banks reconsider their targets and include climate change amongst them, becomes the initial stage in the process.

In his study on greening monetary policy, Kempf (2020) says that the central banks recently became aware that climate change hurts monetary policy transmission via financial risks and has not had time to mobilize. Thus, he proposed integrating climate change mitigation into the monetary policy's primary mission. He illustrates how green monetary policy works out without hampering the inflation range and macroeconomic stabilization targets. This illustration proves that the inclusion of climate change amongst the central bank's targets will not impede the other targets of central banks, such as inflation targeting or macroeconomic stability. Like Campiglio (2016), Kempf (2020) suggests amendments on crediting policies based on counterparties' CO_2 emission levels. Schoenmaker reached a similar conclusion in 2019 in his study of the options of monetary policy greening. He demonstrates how central banks have only considered financial instability aspects of global warming and how they are now starting to account for other aspects of climate change, including the carbon intensity of assets. Finally, Campiglio offers "a tilting approach to steer the Eurosystem's asset and collateral framework towards low carbon assets." All these existing studies depict the essence of setting climate policy micro-targets by central banks into the monetary policy targets while undermining the IMF tools for forecasting.

Nonetheless, Dikau and Volz (2020) conducted a study on IMF's Central Bank Legislation Database by comparing current practices to sustainability-related necessary arrangements and concluded that central banks, anyhow, ought to incorporate physical and transition threats originating from global warming into monetary policy. On a triumphant note, ECB already launched encompassing green monetary policy (Issing, 2020) considering the impact of warming on the financial instability and the sustainability of the environment.

Finally, considering that albeit existing literature effectually describes externalized challenges for forecasting techniques and monetary policy development, it lacks in associating its accuracy with environmental concerns. Thus, this paper is expected to play an original role in the sphere, neglecting the vital relationship between global warming and IMF's accuracy in predictions, further necessitating unusual policy actions.

Methodology

Since the research objective is to identify the relationship between the absolute deviations of forecasts and climate change, estimated coefficients' reliability hereby plays a vital role. Moreover, the variability in deviations is predicted to influence by both players' past values. Taking these factors into account, the path compels us to presume that the study seeks the *dynamic econometric model*. For this purpose, I used the *autoregressive distributed lag (ARDL) model*, inasmuch as it majorly affords the mentioned requirements.

$$\ln(Y)_t = \beta_0 + \beta_1 \ln(X_t) + \beta_2 \ln(Y_{t-1}) + \beta_3 \ln(X_{t-1}) \\ + \dots + \beta_n \ln(Y_{t-w}) + \beta_{n+1} \ln(X_{t-w}) + u_t$$

where $\ln(Y)$ represents the percentage change in the dependent variable, $\ln(X)$ denotes the percentage change in the independent variable, t represents time, u stands for residuals, β are slope parameters in different lags, and w is the number of previous lags.

While employing FP, Central Banks strive to find the equilibrium of the money demand and supply within the inflation target range accompanied by the estimated GDP growth. GDP growth rate, therefore, becomes the projection thresholds for successful policy measures, thus gratifying itself to act as test-takers. As variations in FP's absolute forecast deviations stands as the studied factor, forecast accuracy in GDP will serve as a dependent variable in this context. For representing forecast accuracy, I used Theil U-statistic (Theil, 1966):

$$U = \sqrt{\sum_{t=1}^{t=k} (A_t - F_t)^2 \Big/ \sum_{t=1}^{t=k} {A_t}^2}$$

where F_t represents the percentage change of the forecast for a given time period t, A_t is the percentage change in actual data, and k is the number of data points.

For the independent variable, thesis studies the variations in the level of CO_2 emission both in separate IMF member states and on a global scale as a representative factor of climate change.

Substituting equations into the ARDL model gives us the final version for testing:

$$\ln \sqrt{\sum_{t=1}^{t=k}(A_t - F_t)^2 \Bigg/ \sum_{t=1}^{t=k} {A_t}^2} =$$

$$= \beta_0 + \beta_1 \ln(x_1) + \beta_2 \ln\left(\sqrt{\sum_{t=1}^{t=k}(A_{t-1} - F_{t-1})^2 \Bigg/ \sum_{t=1}^{t=k} {A_{t-1}}^2}\right)$$

$$+ \beta_3 \ln(x_{t-1}) + \cdots + \beta_n \ln\left(\sqrt{\sum_{t=1}^{t=k}(A_{t-w} - F_{t-w})^2 \Bigg/ \sum_{t=1}^{t=k} {A_{t-w}}^2}\right)$$

$$+ \beta_{n+1} \ln(x_{t-w}) + u_t$$

where $\{x, t, u, \beta, w, A, F, k\}$ denote the level of CO_2 emissions, time, residuals, slope parameters, number of previous lags, actual GDP, forecasted GDP, and the number of data points, respectively. Instead of actual and forecasted GDP growth rates [percentage changes as in original U statistic], however, paper inputs data in billions of USD to overcome double percentage count and equalize relevance modules of dependent variables with the independent one.

The study will use EViews software to run the econometric model. The variables and the model are further subject to statistical tests, such as unit root, normality, heteroskedasticity, serial correlation, and misspecification tests. Data collection will follow global and national scales and provided by the International Monetary Fund and the BP.

Data

Study investigations are based on data augmented from IMF and BP databases. Namely, the annual actual and forecasted GDP figures are elicited from IMF's World Economic Outlooks, whereas the CO_2 level numerals are taken from BP's Statistical Review of World Energy (last updated for 2019). For consolidation purposes, the research included only countries with the complete available data in all mentioned sections. For global statistics, it is assumed that databases do not contradict each other in terms of generalization and free from biases.

Carbon dioxide emission levels are calculated in a million tones and represent the last data updated in 2020. The unit of calculation of GDP is billions of USD with current prices. As those current prices are adjusted annually, the actual GDP of a particular year mirrors the available data of that year published during the subsequent year. For instance, the actual GDP for 2006 was published in April of 2007. Regarding the forecasted GDP levels, both two- and six-year forecasts stand for the published year's data. Precisely, the two-year prognosis of 2020 was available in April 2019, whilst the six-year prognosis of 2020 was available in April 2015.

Empirical analysis

For econometric analysis, the study employs EViews statistical software. The empirical analysis path initially examines the global data with the time series, followed by panel data of countries. At EViews, variables are denoted as:

Variables	Abbreviations (Codes)
IMF's GDP forecast accuracy deviation	acc
Carbon dioxide emission levels	co2

Carbon dioxide emission levels are calculated in a million tones, whereas the IMF's GDP forecast accuracy is calculated as:

$$U = \sqrt{\sum_{t=1}^{t=k} (A_t - F_t)^2 \Bigg/ \sum_{t=1}^{t=k} {A_t}^2}$$

where F_t represents the GDP forecast for a given time period t, A_t is the actual GDP in current prices, and k is the number of data points. Otherwise stated, as higher IMF's GDP forecast accuracy deviation (as higher "*acc*"), the less the prognosis is accurate.

Firstly, the global data with two years of forecast accuracies are tested. Subsequent analysis with six-years data and panel data analyses will follow a similar path.

As mentioned earlier, the research is based on the Auto Regressive Distributed Lag model, which has specific prerequisites to be fulfilled. Particularly, analyzed variables must be stationary at the level or the first difference; non-stationary and stationary variables at the second difference are not eligible fundaments for the ARDL model. For testing the stationarity of the variables, the thesis employs Augmented Dickey-Fuller (hereinafter ADF) and Kwiatkowski-Phillips-Schmidt-Shin (hereinafter KPSS) test types. While using ADF test statistic, lag length is set by default for four lags with Akaike Info Criterion (hereinafter AIC) rather than Schwarz Criterion (hereinafter SIC), inasmuch as the sample is restricted to 20 observations. On the other hand, while using KPSS test statistics, the spectral estimation method is set by default as the Bartlett kernel with Newey-West Bandwidth.

When running the ADF test (Appendix 1) at a level for the IMF's global GDP forecast accuracy deviation for two years, the null hypothesis indicates that the series has a unit root, in other words, is non-stationary. However, the probability lower than 0.05 compels to reject the null hypothesis, thereby underlining that the IMF's global GDP forecast accuracy deviation for two years is stationary at level. When running the KPSS test (Appendix 2) at level, the null hypothesis indicates that the variable is stationary. The probability, in this case, is higher than 0.05, which prevents rejecting the null hypothesis, thereby underlining that the IMF's global GDP forecast accuracy for two years is stationary at level. The results of the tests are equivalent.

Similar outcomes are elicited from stationarity tests of the times series of Carbon dioxide emission levels. When running the ADF test (Appendix 3) at a level for the variable, the null hypothesis indicates that the series have a unit root or are non-stationary. The probability lower than 0.05 compels to reject the null hypothesis, underlining that the Carbon dioxide emission levels are stationary at level. KPSS test (Appendix 4), where the null hypothesis indicates that the variable is stationary, illustrates the probability higher than 0.05.

Therefore, the time series of carbon dioxide emission levels are stationary at a level as well. Consequently, both variables are eligible for the ARDL model inclusion.

Nevertheless, the situation with the model describing the IMF's global GDP forecast accuracy deviation for six years is completely different. Unfortunately, the number of observations is restricted to 7 (from 2013 to 2019), preventing unbiased empirical analysis. Although the small sample size leads to failure in statistical tests, the general picture may engender further research with a time span. Figure 2 depicts the possible lagged long-run relationship between two variables, perhaps dictating how the rise in CO_2 emission levels deteriorates the six-year prognoses. This research question will remain trendy for several years until the consolidated and need-affordable data is available.

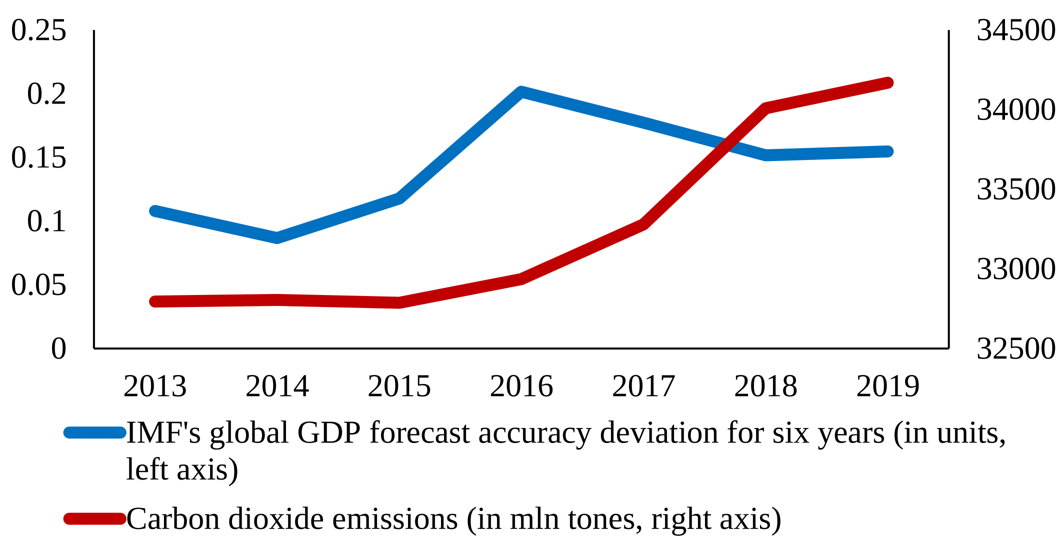

Figure 2. IMF's global GDP forecast accuracy deviation for six years and Carbon dioxide emissions, 2013 – 2019.

IMF's GDP forecast accuracy deviation of the countries for six years is also out of investigation due to the same reasons, albeit engendering vital actuality over the years. Thereby, the paper elucidates statistical analysis on two-year forecasts only.

Upon successful unit test results for variables at the first model with IMF's global GDP forecast accuracy deviation for two years, thesis runs the ARDL model (Appendix 5). The number of lags was automatically selected as 4, with model selection criteria as AIC and ordinary coefficient covariance matrix. With four lags, the model evaluates 16 observations in total, and based on the model selection criteria table (Appendix 6), in which AIC is settled as the primary indicator, ARDL (3,4) is selected as the optimal alternative. R^2 and adjusted R^2 are above 99% and 97%, respectively, illustrating that that change in log forecast accuracy deviation lags and log carbon dioxide emission level lags explain the change in the log forecast accuracy deviation for two years in according manner. F-statistic probability is lower than 0.05, hereby dictating that the short-run relationship model is settled significantly in statistical terms. When eliminating the lags for individual statistical significance, the short-run model is structured in the following form:

$$LOG(ACC) = 2.371 + 0.624*LOG(ACC_{-1}) + 0.002*LOG(CO2_{-4}) + U$$

Formula dictates that though the percentage change in carbon dioxide emission levels does not substantially impact the percentage change in the IMF's global GDP forecast accuracy deviation for two years in economic terms, the first lag of the dependent variable does. By keeping all other variables stable, a 1% increase in the first lagged global GDP forecast accuracy deviation for two years deteriorates the named forecast accuracy (increases GDP forecast accuracy deviation for two years) in the short run by 0.624%, on average.

For long-run relationship estimations, the paper employs the ARDL bounds test (Appendix 7). As it is unequivocal, the F-statistic exceeds the upper bound even at the 1% level of significance. Consequently, the long-run relationship is statistically significant. However, when looking at the ARDL cointegrating and Long Run Form (Appendix 8), there is no variable of individual statistical significance, preventing running the long-run empirical equation. The thesis uses the Wald test to reveal whether there is a joint impact of independent variables. Test results depict that the percentage change in global GDP forecast accuracy deviation lags have a significant joint impact on the percentage change in global GDP forecast accuracy deviation in general (Appendix 9a) [since the probability is less than 0.05, the null hypothesis, which claims no joint impact, is rejected]. In contrast, the percentage change in the carbon dioxide emission levels lags does not (Appendix 9b).

Breusch-Pagan-Godfrey criteria were used to test the heteroskedasticity in the equation (Appendix 10). Results show that the model is free from heteroskedasticity problem since the probability chi-square is higher than 0.05. Thus, thesis fails to reject the null hypothesis, which states homoskedasticity. The normality test results were also positive (Appendix 11), inasmuch as the study failed to reject the null hypothesis expressing that the residuals are normally distributed. Ramsey RESET test (Appendix 12) illustrates that the model is free from the functional form of misspecification too [probability is higher than 0.05]. The study fails to reject the Breusch-Godfrey serial correlation LM test's null hypothesis (Appendix 13), which states that the model is free from the serial correlation problem.

The general outcome from the model above, unbiased in terms of statistical tests, is mentioned in the Findings section.

Subsequently, the paper analyses the panel data of 62 countries, from 2000 to 2019, with the same variables. Model is ARDL; the dependent variable is the percentage change in IMF's GDP forecast accuracy deviation for two years for countries, while the independent ones are the percentage change in forecast accuracy deviation lags and the percentage change in carbon dioxide emission levels. Denotes are similar to the previous model, whereas the number of observations, in this case, equals 1240, therefore, prerequiring distinctive testing criteria.

Initially, the variables are exposed for the unit root tests to examine the stationarity. Once again, the variables are required to be stationary at level or the first difference in order to be eligible for ARDL modeling. While testing variables for stationarity, the study employs individual root – Fischer – ADF test type at the level. Lag length is automatically settled for SIC, fully affording the need for a model with rich data. In other words, compared with the previous model of global estimations, the model with the panel data of countries has several observations, which compels us to prefer SIC over AIC in this particular case. Individual root – Fischer – ADF test null hypothesis claims that the variable has the unit root, or non-stationarity is present. Consequently, for each individual unit root, if the probability is less than 0.05, then the study rejects the null hypothesis of the individual root – Fischer – ADF test and confirms that variables are eligible for the model testing. Appendices 14 and 16 detailly show the individual root – Fischer – ADF test at the level for both variables of the percentage change in IMF's GDP forecast accuracy deviation for two years for countries and the percentage change in carbon dioxide emission levels.

Out of 62 countries, China, India, and Turkey are non-stationary at the level when testing the unit root for the forecast accuracy deviation (Appendix 14). However, at the first difference, no country depicts non-stationarity (Appendix 15). The test outcome proves that the variable "acc" is eligible for the general model.

When it comes to the unit root testing for the carbon dioxide emissions at level (Appendix 16), the vast majority of individual figures compel the study to reject the null hypothesis of the individual root – Fischer – ADF test. On the other hand, vice versa is seen while applying the individual root – Fischer – ADF test at the first difference. Albeit a few exceptions, such as Bangladesh, China, Iceland, Indonesia, Italy, Luxembourg, Malaysia, Mexico, Norway, Philippines, Saudi Arabia, Singapore, Spain, Venezuela, and Vietnam, the remaining countries are eligible for ARDL (Appendix 17). As 24.2% of all countries failed for stationarity testing of the percentage change in carbon dioxide emission levels variable, the study eliminates these countries from the panel data to reserve the unbiasedness. After amendments, by leaving only statistically significant results, the number of the countries participating in the panel data analysis is reduced to 47, while the total number of observations constitutes 940. There is no need to recheck previous tests, whilst the new unit-root test for the explanatory variables cogently depicts that there is no left stationarity challenge to launch the ARDL model (Appendix 18) because all of the individual country probabilities are lower than 0.05, indicating that the null hypothesis of non-stationarity is rejected.

During panel ARDL model estimations, the paper sets the lag number by default as four, with Schwarz criteria, due to the still rich data size. Appendix 19 demonstrates the results of the ARDL test. With statistically significant cointegration in the short run, the model produced the statistically significant long-run equation. Intriguing fact, hereby, is that selecting the ARDL (1,1) model is independent of the criterion asked (Appendix 20).

Unlike in time series, no-obligation upon residual testing is tacked with the panel ARDL model, except the joint relationship analysis, which is impossible with one explanatory variable in regard. Appendix 21 visualizes all short-run individual country cases separately, later consolidated in the next sections. Shortly, the short-run model is out of tact since the main explanatory variable is statistically insignificant (probability is more than 0.05). However, the statistically strong negative cointegration shows that the adjustment is quick in the long term. Thereby, the long-term equation is written as:

$$DLOG(ACC) = -0.661*DLOG(CO2) + U$$

Formula dictates that, ceteris paribus, a 1% increase in carbon dioxide emissions decreases the two-year GDP forecast accuracy deviation of paneled countries by 0.66%, on average. More precise outcomes are described in the sections.

Findings

The empirical analysis aimed to derive four different ARDL models indicating the relationship between the IMF's GDP forecast accuracy and carbon dioxide emission levels. Precisely, the models concentrated on the correlation between IMF's GDP forecast accuracy deviation [of the countries (panel data) and globe (time series), both for two and six years] with its lags and CO_2 lags as explanatory variables. Unfortunately, the study fails to present statistically unbiased outcomes for the six-year forecast accuracy both for time series and panel data due to insufficient observations. It is supposed that after a decade, the literature will be rich enough for sound estimations upon the six-year forecast accuracies while empowering the two-year forecast accuracies as well.

Analysis upon IMF's global GDP forecast accuracy deviation with time series consolidates the statistically significant short-run ARDL model:

$$LOG(ACC) = 2.371 + 0.624*LOG(ACC_{-1}) + 0.002*LOG(CO2_{-4}) + U,$$

where "log(acc)" represents the percentage change in IMF's global GDP forecast accuracy deviation for two years and "log(CO_2)" stands for the percentage change in carbon dioxide emission levels. Therefore, by keeping all other variables stable, a 1% increase in the first lagged two-year global GDP forecast accuracy deviation deteriorates the two-year global GDP forecast accuracy (increases two-year global GDP forecast accuracy deviation) in the short run by 0.624%, on average. Additionally, by keeping all other variables stable, a 1% increase in the fourth lagged carbon dioxide emission level deteriorates the two-year global

GDP forecast accuracy (increases two-year global GDP forecast accuracy deviation) in the short run by 0.002%, on average.

While transferring to the long-term version, it is necessary to focus on the cointegration at bounds test, which is -0.22. This figure, which is also statistically significant, represents the high speed of adjustment to the long-run equilibrium. On the other hand, due to the lack of supportive explanatory variables and inasmuch as the long-term log(co2) is not statistically significant, the paper fails to reflect the long-term equation. All these inclusive analyses demonstrate that in the short term, albeit negligibly in economic terms, climate change deteriorates the IMF's two-year global GDP forecast accuracy with the high-speed adjustability. However, it has no long-term effect on forecast accuracy, at least in the framework of 20 observations. By the same token, the short-run model successfully passed serial correlation, heteroskedasticity, normality, and functional form misspecification tests.

All individual short-run cases illustrate statistically insignificant results when it comes to the panel data, preventing specific micro modeling. A similar path is reflected on the general short-run equation too, where the study fails to reject the null hypothesis that the explanatory variable has no statistically substantial impact on the explained one. However, the cointegration is strong in statistical terms, equals -0.96, and represents the high speed of adjustment to the long-run equilibrium. In comparison with the time series analysis, the long-run equation is strong in panel data analysis and is pictured in this way:

$$DLOG(ACC) = -0.661*DLOG(CO2) + U$$

Ironically, results depict that a 1% increase in carbon dioxide emissions decreases the two-year GDP forecast accuracy deviation of paneled countries by 0.66%, on average. The outcome contradicts the time-series data results for the short run. It is necessary to underline that this model also passed all statistical tests (that panel analysis is obliged to), except the normality test of residual, which is normal due to the high volume of different GDP levels. Albeit insignificant results, all individual LOG(CO2) coefficients, whether negative or positive, are illustrated in figure 3. The reasons for generalized incontinency are discussed in the further section.

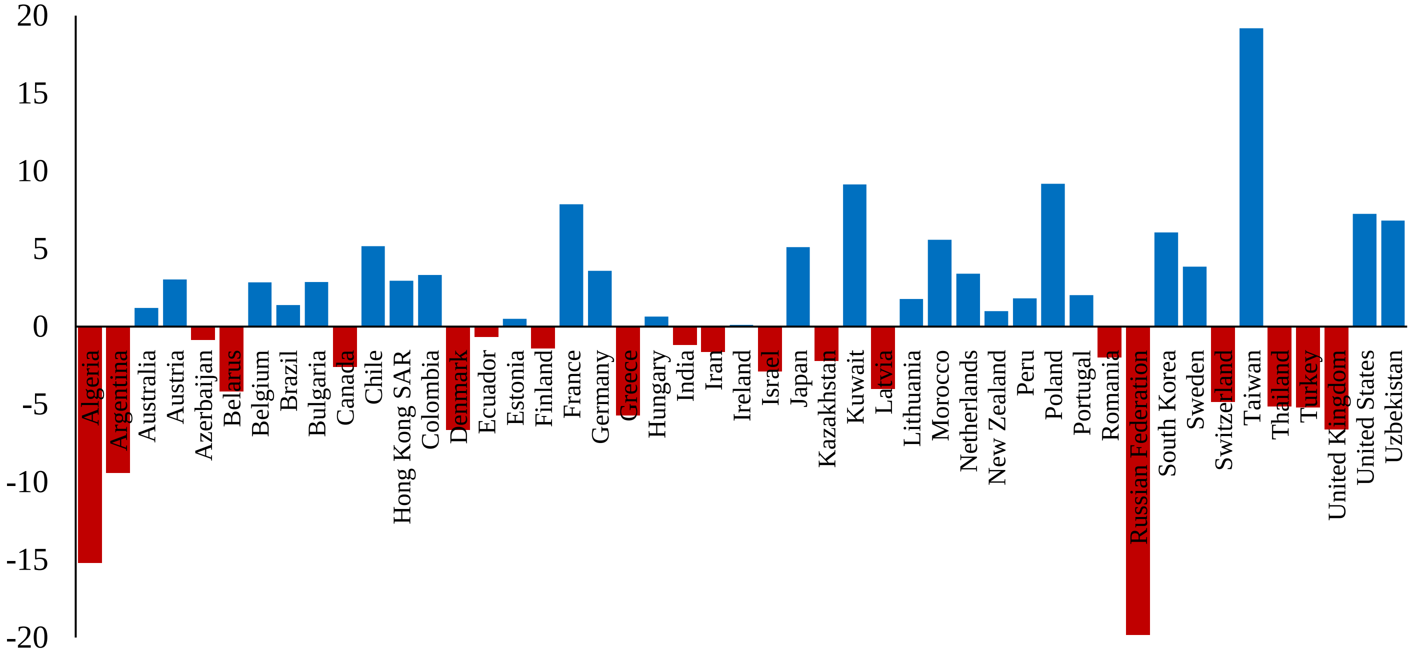

Figure 3. Individual DLOG(CO2) coefficients

Discussion

The general research hypothesis stating that climate change hurts FP's GDP forecast accuracy both in separate states and on a global scale is equivocal: the premise is held for the short-run global time-series data and rejected for the long-run panel data. The status regards only statistically significant results. Additionally, the thesis over-screened insignificant results and elicits these reasons for the outcome inconsistency:

1. Database differences.

One of the first reasons why there were inconsistent outcome was the differences in databases and how they have been compiled. The climate change factor was mirrored in terms of carbon dioxide emission levels given by British Petroleum's Statistical Review of World Energy, whereas the actual and forecasted GDP figures were taken from the IMF's annual World Economic Outlooks. In addition to the difference in database figures, these two organizations also use different methodologies for the data compilation. At this moment, the global data may have critical differences because of some country inconclusiveness. For instance, perhaps a few states account for the global data by the IMF, while not for BP's database. Simultaneously, the methodology of forecasting IMF throughout 20 years may have been modified. These differences have led to the outcome inconsistencies for the short and long run.

2. The number of observations.

Both in panel and time-series data, the number of years is limited to 20. This was done due to the fact that the data over the long-term was not available. This limitation, in its turn, results in certain statistical testing criteria evaluation. When analyzing time series, due to the short sample size, AIC was preferred over SIC while choosing an optimal ARDL model. It is also very likely that since the paper assessed the data for the short-run, the results for the long run were inconsistent. For the panel data, on the other hand, SIC was used, although all tests, in that case, were directing to one model only.

3. Economic insignificance.

Short-run time series and long-run panel analyses may contradict each other. Despite the fact that outcomes are driven for statistically significant fundaments only, equations lack solid economic relations at the end of the day. Coefficients fail to indicate the impact that climate change exert over the forecasting accuracy.

4. Fiscal sector.

When looking at individual country cases, although statistically insignificant, there are severe differences. Literature is rich in studying how climate change affects the fiscal sectors in different states, both positively and negatively. Often included among the positive impact of the climate change is the increased revenue from the taxes collected in agricultural sector as well as the increased economic activity. On the other hand, the negative impact of the climate change on the fiscal sector are the financial crisis. A study by Yale University (Donatelli, 2020) indicated that climate change might make financial crisis twice as likely, costing around 5-10% increases in the government budgets, significant pressure on the fiscal sector. Depending on whether these factors are somehow interrelated, the different impacts of the fiscal sector may also mirror the impact on GDP forecast accuracy.

5. Current prices.

The unit of account for GDP is billion of US dollars in current prices that are adjusted on an annual basis. Thus, the GDP of a particular year mirrors the GDP published the following year for the previous year, e.g., the actual GDP for 2006 was published in April 2007. This way of data identification may vary in quarterly adjustments [GDP publications are often subject to monthly and quarterly revisions], which finally affect the individual country cases.

Furthermore, the paper opens avenues for further research in the field. Notably, after several years, when the data is available, studies are allowed to test similar cases with 40 to 50 observations for the accuracies of 5-6 years. In the future, the data will be available for longer time series, which will make it possible to look longer period observations. The FP prognoses for the short term, such as in this study, may fail to illustrate how climate change factors are crucial while projecting forecasts. Since these forecasts directly impact the macroeconomic planning of each state, an underestimation of ecological alterations may play a vital role in a marginal negative externality. Considering the fact that the climate change and its impact is growing day by day, the impact of the climate change on the FP forecasting might even be greater than overwhelmingly assumed. This makes it fair to argue that further research and study in assessing the impact of the climate change in FP forecasting is extremely important.

Moreover, the thesis puts the carbon dioxide emission levels in the shoes of climate change representative. However, the explanatory variable is augmented for substitution with the global energy consumption in future studies. In other words, authors may freely test the impact of factors like Total Produced Energy on FP forecasts, considering the fact that CO_2 emissions are, anyhow, engendered for energy-producing. Thus, directly or not, the total energy production may be used as a transistor to reveal the impact of ecological factors on macroeconomic diagnostics. On top of that, the literature shows that cryptocurrencies are huge energy demanders[i], thereby increasing global energy consumption immensely.

Consequently, this study may play the role of initiator for future studies intersecting climate change with the construction of macroeconomic prognoses.

Conclusion

Financial Programming, an IMF quantitative framework assisting countries to achieve desired macroeconomic objectives and linking them to policy measures, has circumstance-based restrictions. In spite of the utility of the program, its flaws and restrictions cast doubt on the accuracy and the quality of the forecast made through financial programming. Existing studies afford the need for FP's consistency checks and testing its quality and accuracy. However, the consistency checks and the testing have also been called into question and there are even debates that the methodology does not fare well when it comes to forecasting. The primary critical deficiency of the FP methodology, addressed in this study, is that it does not account for the climate change factor, a critical factor that is gradually making its way into general economic policymaking, including monetary policy. A brief look into the current economic and social policymaking in the world would reveal the growing importance and role that is attached to the climate change. Absence of such a powerful and important factor in the FP methodology further lessens the utility and the applicability of the method. Since climate change is a missing factor in the FP methodology, this research aims to improve the FP tools and the framework by inserting the climate change factor into the analysis. The climate change factor is an essential and – reasonable parameter in this regard because it influences the soundness of the framework by affecting the quality of forecasting and supplementary policy measures.

Although existing literature effectually describes externalized challenges for forecasting techniques and monetary policy development, it lacks in associating its accuracy with environmental concerns. So far, there has not been a single comprehensive study exploring the impact of the climate change on the financial programming forecasting accuracy. Thus, this paper plays an original role in the sphere, seeking to uncover the vital relationship between global warming and the IMF's accuracy in predictions. Moving from this premise, the research objective is to identify whether there is a relationship between the absolute deviations of FP forecasted values and climate change. It is hoped that the paper will pave the way for further research into this topic with more available data and better modelling and analysis tools in the future.

Under the climate change variable, the study tracks CO_2 emissions on both global and separately national scales. The national data pertaining to the climate change has been assessed in combination with the data collected at the global context. Consequently, the research question is how the CO_2 emissions affect the FP's GDP forecasting accuracy.

Since the research objective is to identify the relationship between the absolute deviations of forecasts and climate change, and the variability in deviations is predicted to influence both players' past values, the thesis presumed autoregressive distributed lag (ARDL) model as a basis for the empirical research methodology. The study employed EViews software to run the econometric models.

The paper designed four distinctive models with CO_2 emissions and FP's two (1)/ six (2)-year global (3) and panel (4) GDP forecasting accuracies. It is necessary to underline that after the consolidation processes, the total number of examined countries in the panel was reduced to 47 from 62. Unfortunately, IMF's global and panel GDP forecast accuracy deviation of the countries for six years is out of investigation due to the small sample size, albeit engendering vital actuality over the years. Thereby, the paper elucidates statistical analysis on two-year forecasts only.

The findings of time-series analysis show that by keeping all other variables stable, a 1% increase in the first lagged global GDP forecast accuracy deviation for two years deteriorates the named forecast accuracy (increases GDP forecast accuracy deviation for two years) in the short run by 0.624%, on average:

$$LOG(ACC) = 2.371 + 0.624*LOG(ACC_{-1}) + 0.002*LOG(CO2_{-4}) + U$$

where "log(acc)" represents the percentage change in IMF's global GDP forecast accuracy deviation for two years and "log(CO_2)" stands for the percentage change in carbon dioxide emission levels. However, though statistically significant, the CO_2 emissions do not substantially affect two-year global GDP forecast accuracy in economic terms.

On the other hand, the findings of the panel data dictate that ceteris paribus, a 1% increase in carbon dioxide emissions decreases the two-year GDP forecast accuracy deviation of paneled countries by 0.66%, on average:

$$DLOG(ACC) = -0.661*DLOG(CO2) + U$$

Finally, the outcomes of the two models minorly contradict each other. Database differences - global data may have critical differences because of some country inconclusiveness from different sources, the number of observations - the limitation in terms of 20 years results in different statistical testing criteria, economic significance - equations lack solid economic relations, fiscal sector - the different impacts of the fiscal sector may also mirror the impact on GDP forecast accuracy, and current prices - data identification may vary in quarterly adjustments may serve as the reasons for this inconsistency.

In conclusion, the thesis shows that neither in the short term nor in the long, the CO_2 emissions significantly affect the FP's global two-year GDP forecasting accuracy. Therefore, albeit rejected research hypothesis, this study may play the role of initiator for future studies intersecting climate change with the construction of macroeconomic prognoses.

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Appendices

Appendix 1.

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.096066	0.0487
Test critical values:	1% level	-3.959148	
	5% level	-3.081002	
	10% level	-2.681330	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 15

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ACC)
Method: Least Squares
Date: 04/18/21 Time: 02:27
Sample (adjusted): 2005 2019
Included observations: 15 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ACC(-1)	-0.261307	0.084400	-3.096066	0.0128
D(ACC(-1))	-0.034942	0.235634	-0.148289	0.8854
D(ACC(-2))	-0.516157	0.244398	-2.111956	0.0639
D(ACC(-3))	-0.047216	0.240000	-0.196733	0.8484
D(ACC(-4))	-0.415321	0.220579	-1.882868	0.0924
C	9234.383	2863.776	3.224547	0.0104

R-squared	0.579555	Mean dependent var	472.7651
Adjusted R-squared	0.345974	S.D. dependent var	523.3316
SE of regression	423.2279	Akaike info criterion	15.22287
Sum squared resid	1612097.	Schwarz criterion	15.50609
Log likelihood	-108.1715	Hannan-Quinn criter.	15.21986
F-statistic	2.481178	Durbin-Watson stat	2.467107
Prob(F-statistic)	0.111787		

Appendix 2.

Null Hypothesis: ACC is stationary
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.587057
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	1114667 4
HAC corrected variance (Bartlett kernel)	3564978 7

KPSS Test Equation
Dependent Variable: ACC
Method: Least Squares
Date: 04/18/21 Time: 02:32
Sample: 2000 2019
Included observations: 20

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	30033.43	765.9419	39.21111	0.0000

R-squared	0.000000	Mean dependent var	30033.43
Adjusted R-squared	0.000000	S.D. dependent var	3425.396
SE of regression	3425.396	Akaike info criterion	19.16453
Sum squared resid	2.23E+08	Schwarz criterion	19.21432
Log likelihood	-190.6453	Hannan-Quinn criter.	19.17425
Durbin-Watson stat	0.048425		

Appendix 3.

Null Hypothesis: CO2 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.915994	0.0084
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2)
Method: Least Squares
Date: 04/18/21 Time: 02:47
Sample (adjusted): 2001 2019
Included observations: 19 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2(-1)	-0.908806	0.232075	-3.915994	0.0011
C	0.056834	0.017167	3.310632	0.0041

R-squared	0.474254	Mean dependent var	0.002834
Adjusted R-squared	0.443328	S.D. dependent var	0.059738
SE of regression	0.044571	Akaike info criterion	-3.284187
Sum squared resid	0.033771	Schwarz criterion	-3.184773
Log likelihood	33.19978	Hannan-Quinn criter.	-3.267363
F-statistic	15.33501	Durbin-Watson stat	1.836433
Prob(F-statistic)	0.001112		

Appendix 4.

Null Hypothesis: CO2 is stationary
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.167768
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.001844
HAC corrected variance (Bartlett kernel)	0.002012

KPSS Test Equation
Dependent Variable: CO2
Method: Least Squares
Date: 04/18/21 Time: 02:48
Sample: 2000 2019
Included observations: 20

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.059533	0.009853	6.042290	0.0000

R-squared	0.000000	Mean dependent var	0.059533
Adjusted R-squared	0.000000	S.D. dependent var	0.044063
SE of regression	0.044063	Akaike info criterion	-3.357702
Sum squared resid	0.036889	Schwarz criterion	-3.307915
Log likelihood	34.57702	Hannan-Quinn criter.	-3.347983
Durbin-Watson stat	1.745435		

Appendix 5.

Dependent Variable: LOG(ACC)
Method: ARDL
Date: 04/19/21 Time: 02:26
Sample (adjusted): 2004 2019
Included observations: 16 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): LOG(CO2)
Fixed regressors: C
Number of models evaluated: 20
Selected Model: ARDL(3, 4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LOG(ACC(-1))	0.623532	0.191103	3.262810	0.0138
LOG(ACC(-2))	-0.079554	0.244828	-0.324938	0.7547
LOG(ACC(-3))	0.230492	0.188131	1.225166	0.2601
LOG(CO2)	9.98E-05	0.000777	0.128500	0.9014
LOG(CO2(-1))	0.000138	0.000737	0.187907	0.8563
LOG(CO2(-2))	7.20E-06	0.000661	0.010897	0.9916
LOG(CO2(-3))	0.000993	0.000622	1.595704	0.1546
LOG(CO2(-4))	0.002438	0.000642	3.797978	0.0067
C	2.371495	0.448874	5.283207	0.0011

R-squared	0.990624	Mean dependent var	10.35291
Adjusted R-squared	0.979909	S.D. dependent var	0.068954
SE of regression	0.009774	Akaike info criterion	-6.119928
Sum squared resid	0.000669	Schwarz criterion	-5.685347
Log likelihood	57.95942	Hannan-Quinn criter.	-6.097674
F-statistic	92.45198	Durbin-Watson stat	1.327558
Prob(F-statistic)	0.000002		

*Note: p-values and any subsequent tests do not account for model selection.

Appendix 6.

Model Selection Criteria Table
Dependent Variable: LOG(ACC)
Date: 04/19/21 Time: 02:37
Sample: 2000 2019
Included observations: 16

Model	LogL	AIC*	BIC	HQ	Adj. R-sq	Specification
6	57.959422	-6.119928	-5.685347	-6.097674	0.979909	ARDL(3, 4)
16	55.750870	-6.093859	-5.755851	-6.076550	0.979406	ARDL(1, 4)
11	56.405203	-6.050650	-5.664356	-6.030869	0.978651	ARDL(2, 4)
1	57.986989	-5.998374	-5.515506	-5.973647	0.976642	ARDL(4, 4)
20	46.159849	-5.394981	-5.250121	-5.387563	0.952716	ARDL(1, 0)
10	47.798833	-5.349854	-5.108420	-5.337491	0.954471	ARDL(3, 0)
15	46.184129	-5.273016	-5.079869	-5.263125	0.948931	ARDL(2, 0)
19	46.160286	-5.270036	-5.076889	-5.260145	0.948779	ARDL(1, 1)
9	48.138140	-5.267267	-4.977547	-5.252431	0.951998	ARDL(3, 1)
8	48.861475	-5.232684	-4.894677	-5.215376	0.951275	ARDL(3, 2)
5	47.807354	-5.225919	-4.936198	-5.211083	0.949972	ARDL(4, 0)
3	49.451476	-5.181435	-4.795140	-5.161653	0.949082	ARDL(4, 2)
18	46.245165	-5.155646	-4.914212	-5.143282	0.944712	ARDL(1, 2)
4	48.213831	-5.151729	-4.813721	-5.134420	0.947167	ARDL(4, 1)
14	46.184136	-5.148017	-4.906583	-5.135654	0.944289	ARDL(2, 1)
7	49.010370	-5.126296	-4.740002	-5.106515	0.946196	ARDL(3, 3)
17	46.772181	-5.096523	-4.806802	-5.081687	0.943061	ARDL(1, 3)
2	49.453236	-5.056655	-4.622073	-5.034400	0.941821	ARDL(4, 3)
13	46.277468	-5.034683	-4.744963	-5.019847	0.939429	ARDL(2, 2)
12	46.775474	-4.971934	-4.633927	-4.954626	0.936760	ARDL(2, 3)

Appendix 7.

ARDL Bounds Test
Date: 04/19/21 Time: 02:59
Sample: 2004 2019
Included observations: 16
Null Hypothesis: No long-run relationships exist

Test Statistic	Value	k
F-statistic	14.51976	1

Critical Value Bounds

Significance	I0 Bound	I1 Bound
10%	4.04	4.78
5%	4.94	5.73
2.5%	5.77	6.68
1%	6.84	7.84

Test Equation:
Dependent Variable: DLOG(ACC)
Method: Least Squares
Date: 04/19/21 Time: 02:59
Sample: 2004 2019
Included observations: 16

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(ACC(-1))	-0.150938	0.166004	-0.909244	0.3934
DLOG(ACC(-2))	-0.230492	0.188131	-1.225166	0.2601
DLOG(CO2)	9.98E-05	0.000777	0.128500	0.9014
DLOG(CO2(-1))	-0.003438	0.001400	-2.456207	0.0437
DLOG(CO2(-2))	-0.003431	0.001003	-3.420600	0.0111
DLOG(CO2(-3))	-0.002438	0.000642	-3.797978	0.0067
C	2.371495	0.448874	5.283207	0.0011
LOG(CO2(-1))	0.003677	0.002414	1.523094	0.1716
LOG(ACC(-1))	-0.225530	0.043112	-5.231315	0.0012

R-squared	0.877940	Mean dependent var	0.017638
Adjusted R-squared	0.738442	S.D. dependent var	0.019111
SE of regression	0.009774	Akaike info criterion	-6.119928
Sum squared resid	0.000669	Schwarz criterion	-5.685347
Log likelihood	57.95942	Hannan-Quinn criter.	-6.097674
F-statistic	6.293579	Durbin-Watson stat	1.327558
Prob(F-statistic)	0.012651		

Appendix 8.

ARDL Cointegrating And Long Run Form
Dependent Variable: LOG(ACC)
Selected Model: ARDL(3, 4)
Date: 04/19/21 Time: 03:07
Sample: 2000 2019
Included observations: 16

Cointegrating Form

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(ACC(-1))	-0.150938	0.166004	-0.909244	0.3934
DLOG(ACC(-2))	-0.230492	0.188131	-1.225166	0.2601
DLOG(CO2)	0.000100	0.000777	0.128500	0.9014
DLOG(CO2(-1))	-0.000007	0.000661	-0.010897	0.9916
DLOG(CO2(-2))	-0.000993	0.000622	-1.595704	0.1546
DLOG(CO2(-3))	-0.002438	0.000642	-3.797978	0.0067
CointEq(-1)	-0.225530	0.043112	-5.231315	0.0012

Cointeq = LOG(ACC) - (0.0163*LOG(CO2) + 10.5152)

Long Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(CO2)	0.016302	0.011015	1.480016	0.1824
C	10.515193	0.041274	254.762697	0.0000

Appendix 9a.

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	7.206025	(2, 7)	0.0200
Chi-square	14.41205	2	0.0007

Null Hypothesis: C(1)=C(2)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)	0.623532	0.191103
C(2)	-0.079554	0.244828

Restrictions are linear in coefficients.

Appendix 9b.

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	0.726539	(4, 7)	0.6012
Chi-square	2.906155	4	0.5737

Null Hypothesis: C(3)=C(4)=C(5)=C(6)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(3)	0.230492	0.188131
C(4)	9.98E-05	0.000777
C(5)	0.000138	0.000737
C(6)	7.20E-06	0.000661

Restrictions are linear in coefficients.

Appendix 10.

Heteroskedasticity Test: Breusch-Pagan-Godfrey

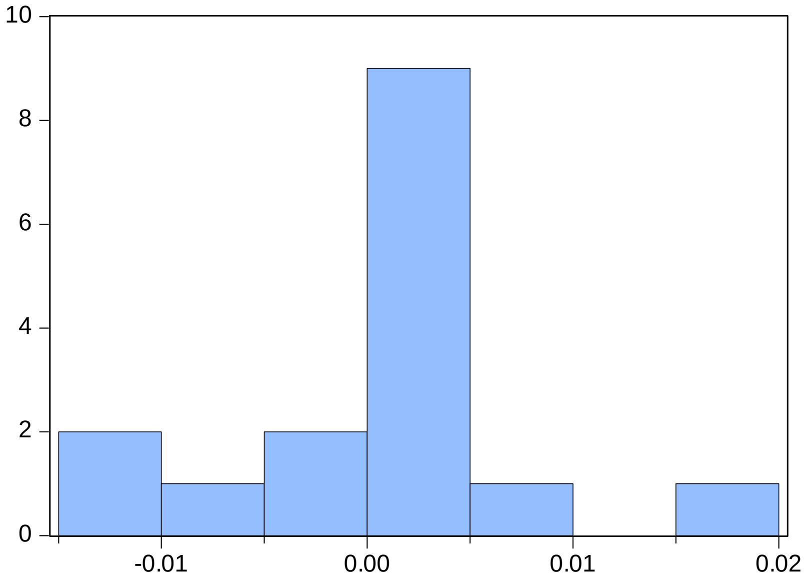
F-statistic	0.249252	Prob. F(8,7)	0.9651
Obs*R-squared	3.547280	Prob. Chi-Square(8)	0.8955
Scaled explained SS	1.077907	Prob. Chi-Square(8)	0.9977

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 04/19/21 Time: 04:54
Sample: 2004 2019
Included observations: 16

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002529	0.004562	-0.554437	0.5965
LOG(ACC(-1))	-0.000355	0.001942	-0.182965	0.8600
LOG(ACC(-2))	-0.000381	0.002488	-0.152991	0.8827
LOG(ACC(-3))	0.000985	0.001912	0.515462	0.6221
LOG(CO2)	-2.91E-06	7.89E-06	-0.368239	0.7236
LOG(CO2(-1))	-2.46E-06	7.49E-06	-0.329284	0.7516
LOG(CO2(-2))	-1.41E-06	6.71E-06	-0.210106	0.8396
LOG(CO2(-3))	9.63E-07	6.32E-06	0.152207	0.8833
LOG(CO2(-4))	-6.00E-08	6.52E-06	-0.009193	0.9929

R-squared	0.221705	Mean dependent var	4.18E-05
Adjusted R-squared	-0.667775	S.D. dependent var	7.69E-05
SE of regression	9.93E-05	Akaike info criterion	-15.29804
Sum squared resid	6.91E-08	Schwarz criterion	-14.86346
Log likelihood	131.3843	Hannan-Quinn criter.	-15.27578
F-statistic	0.249252	Durbin-Watson stat	2.564707
Prob(F-statistic)	0.965082		

Appendix 11.



Series: Residuals	
Sample 2004 2019	
Observations 16	
Mean	-1.78e-15
Median	0.000742
Maximum	0.016507
Minimum	-0.012450
Std. Dev.	0.006677
Skewness	0.253412
Kurtosis	4.175116
Jarque-Bera	1.091846
Probability	0.579307

Appendix 12.

Ramsey RESET Test
Equation: UNTITLED
Specification: LOG(ACC) LOG(ACC(-1)) LOG(ACC(-2)) LOG(ACC(-3))
LOG(CO2) LOG(CO2(-1)) LOG(CO2(-2)) LOG(CO2(-3)) LOG(CO2(-4))
C
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	0.547998	6	0.6035
F-statistic	0.300302	(1, 6)	0.6035

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	3.19E-05	1	3.19E-05
Restricted SSR	0.000669	7	9.55E-05
Unrestricted SSR	0.000637	6	0.000106

Unrestricted Test Equation:
Dependent Variable: LOG(ACC)

Method: ARDL
Date: 04/19/21 Time: 05:14
Sample: 2004 2019
Included observations: 16
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic):
Fixed regressors: C

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LOG(ACC(-1))	6.076297	9.952373	0.610538	0.5639
LOG(ACC(-2))	-0.803832	1.346638	-0.596917	0.5724
LOG(ACC(-3))	2.241317	3.674756	0.609923	0.5643
LOG(CO2)	0.001008	0.001849	0.545323	0.6052
LOG(CO2(-1))	0.001448	0.002512	0.576265	0.5854
LOG(CO2(-2))	0.000203	0.000782	0.259033	0.8043
LOG(CO2(-3))	0.009785	0.016058	0.609385	0.5646
LOG(CO2(-4))	0.023740	0.038878	0.610626	0.5638
C	-21.93549	44.35847	-0.494505	0.6385
FITTED^2	-0.421173	0.768567	-0.547998	0.6035

R-squared	0.991071	Mean dependent var	10.35291
Adjusted R-squared	0.977678	S.D. dependent var	0.068954
SE of regression	0.010302	Akaike info criterion	-6.043766
Sum squared resid	0.000637	Schwarz criterion	-5.560898
Log likelihood	58.35013	Hannan-Quinn criter.	-6.019039
F-statistic	73.99850	Durbin-Watson stat	1.276766
Prob(F-statistic)	0.000019		

*Note: p-values and any subsequent tests do not account for model selection.

Appendix 13.

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.953170	Prob. F(2,5)	0.4460
Obs*R-squared	4.416441	Prob. Chi-Square(2)	0.1099

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 04/19/21 Time: 05:18
Sample: 2004 2019
Included observations: 16
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(ACC(-1))	-0.150459	0.231717	-0.649322	0.5448
LOG(ACC(-2))	0.241686	0.312643	0.773042	0.4744
LOG(ACC(-3))	-0.112057	0.250154	-0.447951	0.6729
LOG(CO2)	-2.99E-06	0.000891	-0.003350	0.9975
LOG(CO2(-1))	0.000282	0.000894	0.315296	0.7653
LOG(CO2(-2))	0.000115	0.000711	0.162050	0.8776
LOG(CO2(-3))	3.28E-05	0.000654	0.050150	0.9619
LOG(CO2(-4))	0.000181	0.000673	0.268980	0.7987
C	0.217429	0.484071	0.449168	0.6721
RESID(-1)	0.670789	0.509789	1.315818	0.2453
RESID(-2)	-0.692836	0.760339	-0.911219	0.4040

R-squared	0.276028	Mean dependent var	-1.78E-15
Adjusted R-squared	-1.171917	S.D. dependent var	0.006677
SE of regression	0.009840	Akaike info criterion	-6.192930
Sum squared resid	0.000484	Schwarz criterion	-5.661775
Log likelihood	60.54344	Hannan-Quinn criter.	-6.165730
F-statistic	0.190634	Durbin-Watson stat	2.224165
Prob(F-statistic)	0.987288		

Appendix 14.

Null Hypothesis: Unit root (individual unit root process)
Series: ACC
Date: 04/20/21 Time: 01:33
Sample: 2000 2019
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Total number of observations: 1147
Cross-sections included: 62

Method	Statistic	Prob.**
ADF - Fisher Chi-square	687.335	0.0000
ADF - Choi Z-stat	-20.1180	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results ACC

Cross section	Prob.	Lag	Max Lag	Obs
Algeria	0.0010	1	4	18
Argentina	0.0054	0	4	19
Australia	0.0033	0	4	19
Austria	0.0007	0	4	19
Azerbaijan	0.0353	1	4	18
Bangladesh	0.0135	1	4	18
Belarus	0.0043	1	4	18
Belgium	0.0006	1	4	18
Brazil	0.0021	0	4	19
Bulgaria	0.0237	0	4	19
Canada	0.0055	1	4	18
Chile	0.0034	0	4	19
China	0.2488	0	4	19
Hong Kong SAR	0.0074	0	4	19
Colombia	0.0117	3	4	16
Denmark	0.0003	1	4	18
Ecuador	0.0295	1	4	18
Estonia	0.0012	0	4	19
Finland	0.0011	0	4	19
France	0.0012	1	4	18

Germany	0.0029	0	4	19
Greece	0.0035	0	4	19
Hungary	0.0034	0	4	19
Iceland	0.0003	0	4	19
India	0.8156	4	4	15
Indonesia	0.0043	0	4	19
Iran	0.0064	0	4	19
Ireland	0.0022	0	4	19
Israel	0.0151	0	4	19
Italy	0.0001	1	4	18
Japan	0.0137	0	4	19
Kazakhstan	0.0046	2	4	17
Kuwait	0.0317	0	4	19
Latvia	0.0065	0	4	19
Lithuania	0.0050	0	4	19
Luxembourg	0.0062	0	4	19
Malaysia	0.0109	1	4	18
Mexico	0.0020	0	4	19
Morocco	0.0018	0	4	19
Netherlands	0.0005	1	4	18
New Zealand	0.0496	0	4	19
Norway	0.0073	1	4	18
Peru	0.0055	0	4	19
Philippines	0.0401	0	4	19
Poland	0.0024	0	4	19
Portugal	0.0002	1	4	18
Romania	0.0092	0	4	19
Russian Federation	0.0073	3	4	16
Saudi Arabia	0.0043	0	4	19
Singapore	0.0263	0	4	19
South Korea	0.0264	1	4	18
Spain	0.0023	1	4	18
Sweden	0.0024	0	4	19
Switzerland	0.0070	0	4	19
Taiwan	0.0277	0	4	19
Thailand	0.0147	0	4	19
Turkey	0.0696	0	4	19
United Kingdom	0.0012	0	4	19
United States of America	0.0006	0	4	19
Uzbekistan	0.0000	0	4	19
Venezuela	0.0160	0	4	19
Vietnam	0.0045	3	4	16

Appendix 15.

Null Hypothesis: Unit root (individual unit root process)
Series: D(ACC)
Date: 04/20/21 Time: 01:43
Sample: 2000 2019
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Total number of observations: 1058
Cross-sections included: 62

Method	Statistic	Prob.**
ADF - Fisher Chi-square	1030.80	0.0000
ADF - Choi Z-stat	-26.8403	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results D(ACC)

Cross section	Prob.	Lag	Max Lag	Obs
Algeria	0.0034	2	3	16
Argentina	0.0000	0	3	18
Australia	0.0000	0	3	18
Austria	0.0029	2	3	16
Azerbaijan	0.0034	0	3	18
Bangladesh	0.0061	2	3	16
Belarus	0.0003	1	3	17
Belgium	0.0012	2	3	16
Brazil	0.0046	3	3	15
Bulgaria	0.0004	1	3	17
Canada	0.0061	3	3	15
Chile	0.0019	2	3	16
China	0.0007	0	3	18
Hong Kong SAR	0.0002	0	3	18
Colombia	0.0183	3	3	15
Denmark	0.0000	1	3	17
Ecuador	0.0259	2	3	16
Estonia	0.0005	1	3	17
Finland	0.0046	2	3	16
France	0.0000	1	3	17

Germany	0.0000	0	3	18
Greece	0.0000	0	3	18
Hungary	0.0000	0	3	18
Iceland	0.0000	0	3	18
India	0.0291	3	3	15
Indonesia	0.0000	1	3	17
Iran	0.0003	0	3	18
Ireland	0.0000	0	3	18
Israel	0.0017	1	3	17
Italy	0.0000	1	3	17
Japan	0.0000	0	3	18
Kazakhstan	0.0022	2	3	16
Kuwait	0.0037	1	3	17
Latvia	0.0000	0	3	18
Lithuania	0.0000	0	3	18
Luxembourg	0.0001	1	3	17
Malaysia	0.0010	1	3	17
Mexico	0.0001	0	3	18
Morocco	0.0000	0	3	18
Netherlands	0.0017	2	3	16
New Zealand	0.0016	0	3	18
Norway	0.0046	0	3	18
Peru	0.0008	0	3	18
Philippines	0.0002	0	3	18
Poland	0.0006	1	3	17
Portugal	0.0017	2	3	16
Romania	0.0006	1	3	17
Russian Federation	0.0001	0	3	18
Saudi Arabia	0.0000	1	3	17
Singapore	0.0004	0	3	18
South Korea	0.0019	1	3	17
Spain	0.0006	2	3	16
Sweden	0.0051	1	3	17
Switzerland	0.0000	1	3	17
Taiwan	0.0003	0	3	18
Thailand	0.0001	1	3	17
Turkey	0.0047	3	3	15
United Kingdom	0.0057	3	3	15
United States of America	0.0000	0	3	18
Uzbekistan	0.0000	0	3	18
Venezuela	0.0000	0	3	18
Vietnam	0.0119	0	3	18

Appendix 16.

Null Hypothesis: Unit root (individual unit root process)
Series: CO_2
Date: 04/20/21 Time: 01:49
Sample: 2000 2019
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Total number of observations: 1144
Cross-sections included: 62

Method	Statistic	Prob.**
ADF - Fisher Chi-square	107.672	0.8516
ADF - Choi Z-stat	4.41175	1.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results CO_2

Cross section	Prob.	Lag	Max Lag	Obs
Algeria	0.9977	0	4	19
Argentina	0.7112	0	4	19
Australia	0.5310	0	4	19
Austria	0.1284	3	4	16
Azerbaijan	0.2001	1	4	18
Bangladesh	1.0000	3	4	16
Belarus	0.4466	0	4	19
Belgium	0.7659	1	4	18
Brazil	0.6888	0	4	19
Bulgaria	0.1539	0	4	19
Canada	0.0503	0	4	19
Chile	0.7729	0	4	19
China	0.0874	0	4	19
Hong Kong SAR	0.1522	2	4	17
Colombia	0.9796	1	4	18
Denmark	0.9828	2	4	17
Ecuador	0.6658	0	4	19
Estonia	0.3544	2	4	17
Finland	0.9555	2	4	17
France	0.9233	0	4	19

Germany	0.9204	0	4	19
Greece	0.9761	0	4	19
Hungary	0.7672	0	4	19
Iceland	0.0304	1	4	18
India	0.9942	1	4	18
Indonesia	0.9729	0	4	19
Iran	0.8561	0	4	19
Ireland	0.8427	0	4	19
Israel	0.1909	0	4	19
Italy	0.9301	0	4	19
Japan	0.3555	0	4	19
Kazakhstan	0.6078	0	4	19
Kuwait	0.4115	0	4	19
Latvia	0.0153	0	4	19
Lithuania	0.1264	0	4	19
Luxembourg	0.1808	1	4	18
Malaysia	0.0903	1	4	18
Mexico	0.2818	2	4	17
Morocco	0.9414	0	4	19
Netherlands	0.9358	0	4	19
New Zealand	0.0456	0	4	19
Norway	0.9312	2	4	17
Peru	0.9317	0	4	19
Philippines	1.0000	0	4	19
Poland	0.1380	0	4	19
Portugal	0.5985	0	4	19
Romania	0.8327	0	4	19
Russian Federation	0.0385	0	4	19
Saudi Arabia	0.5457	0	4	19
Singapore	0.7665	1	4	18
South Korea	0.5978	0	4	19
Spain	0.8086	0	4	19
Sweden	0.8815	0	4	19
Switzerland	0.9956	3	4	16
Taiwan	0.0464	1	4	18
Thailand	0.2941	0	4	19
Turkey	0.9375	0	4	19
United Kingdom	0.9851	0	4	19
United States of America	0.8332	0	4	19
Uzbekistan	0.3751	0	4	19
Venezuela	0.8651	2	4	17
Vietnam	1.0000	2	4	17

Appendix 17.

Null Hypothesis: Unit root (individual unit root process)
Series: D(CO2)
Date: 04/20/21 Time: 01:51
Sample: 2000 2019
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Total number of observations: 1093
Cross-sections included: 62

Method	Statistic	Prob.**
ADF - Fisher Chi-square	643.155	0.0000
ADF - Choi Z-stat	-18.3898	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results D(CO2)

Cross section	Prob.	Lag	Max Lag	Obs
Algeria	0.0124	1	3	17
Argentina	0.0347	0	3	18
Australia	0.0066	0	3	18
Austria	0.0003	0	3	18
Azerbaijan	0.0499	0	3	18
Bangladesh	0.9447	3	3	15
Belarus	0.0495	2	3	16
Belgium	0.0000	0	3	18
Brazil	0.0229	0	3	18
Bulgaria	0.0015	1	3	17
Canada	0.0001	1	3	17
Chile	0.0072	0	3	18
China	0.3427	0	3	18
Hong Kong SAR	0.0000	0	3	18
Colombia	0.0002	0	3	18
Denmark	0.0015	1	3	17
Ecuador	0.0279	0	3	18
Estonia	0.0005	1	3	17
Finland	0.0007	1	3	17
France	0.0005	0	3	18

Germany	0.0002	0	3	18
Greece	0.0409	0	3	18
Hungary	0.0115	0	3	18
Iceland	0.2928	0	3	18
India	0.0049	0	3	18
Indonesia	0.0588	0	3	18
Iran	0.0144	0	3	18
Ireland	0.0050	0	3	18
Israel	0.0008	0	3	18
Italy	0.0535	0	3	18
Japan	0.0007	0	3	18
Kazakhstan	0.0056	1	3	17
Kuwait	0.0034	0	3	18
Latvia	0.0001	0	3	18
Lithuania	0.0002	0	3	18
Luxembourg	0.1185	0	3	18
Malaysia	0.3684	1	3	17
Mexico	0.1991	1	3	17
Morocco	0.0006	0	3	18
Netherlands	0.0018	0	3	18
New Zealand	0.0000	0	3	18
Norway	0.0509	1	3	17
Peru	0.0022	0	3	18
Philippines	0.2187	0	3	18
Poland	0.0029	0	3	18
Portugal	0.0011	0	3	18
Romania	0.0086	0	3	18
Russian Federation	0.0032	2	3	16
Saudi Arabia	0.0953	0	3	18
Singapore	0.1896	0	3	18
South Korea	0.0355	0	3	18
Spain	0.0663	0	3	18
Sweden	0.0029	0	3	18
Switzerland	0.0003	2	3	16
Taiwan	0.0162	1	3	17
Thailand	0.0146	0	3	18
Turkey	0.0059	1	3	17
United Kingdom	0.0005	0	3	18
United States of America	0.0052	1	3	17
Uzbekistan	0.0001	0	3	18
Venezuela	0.5957	1	3	17
Vietnam	0.1644	0	3	18

Appendix 18.

Null Hypothesis: Unit root (individual unit root process)
Series: D(CO2)
Date: 04/20/21 Time: 02:37
Sample: 2000 2019
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 2
Total number of observations: 830
Cross-sections included: 47

Method	Statistic	Prob.**
ADF - Fisher Chi-square	590.331	0.0000
ADF - Choi Z-stat	-19.4099	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results D(CO2)

Cross section	Prob.	Lag	Max Lag	Obs
Algeria	0.0124	1	3	17
Argentina	0.0347	0	3	18
Australia	0.0066	0	3	18
Austria	0.0003	0	3	18
Azerbaijan	0.0499	0	3	18
Belarus	0.0495	2	3	16
Belgium	0.0000	0	3	18
Brazil	0.0229	0	3	18
Bulgaria	0.0015	1	3	17
Canada	0.0001	1	3	17
Chile	0.0072	0	3	18
Hong Kong SAR	0.0000	0	3	18
Colombia	0.0002	0	3	18
Denmark	0.0015	1	3	17
Ecuador	0.0279	0	3	18
Estonia	0.0005	1	3	17
Finland	0.0007	1	3	17
France	0.0005	0	3	18
Germany	0.0002	0	3	18
Greece	0.0409	0	3	18

Hungary	0.0115	0	3	18
India	0.0049	0	3	18
Iran	0.0144	0	3	18
Ireland	0.0050	0	3	18
Israel	0.0008	0	3	18
Japan	0.0007	0	3	18
Kazakhstan	0.0056	1	3	17
Kuwait	0.0034	0	3	18
Latvia	0.0001	0	3	18
Lithuania	0.0002	0	3	18
Morocco	0.0006	0	3	18
Netherlands	0.0018	0	3	18
New Zealand	0.0000	0	3	18
Peru	0.0022	0	3	18
Poland	0.0029	0	3	18
Portugal	0.0011	0	3	18
Romania	0.0086	0	3	18
Russian Federation	0.0032	2	3	16
South Korea	0.0355	0	3	18
Sweden	0.0029	0	3	18
Switzerland	0.0003	2	3	16
Taiwan	0.0162	1	3	17
Thailand	0.0146	0	3	18
Turkey	0.0059	1	3	17
United Kingdom	0.0005	0	3	18
United States of America	0.0052	1	3	17
Uzbekistan	0.0001	0	3	18

Appendix 19.

Dependent Variable: DLOG(ACC)
Method: ARDL
Date: 04/20/21 Time: 02:42
Sample: 2001 2019
Included observations: 893
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Schwarz criterion (SIC)
Dynamic regressors (4 lags, automatic): LOG(CO2)
Fixed regressors: C
Number of models evaluated: 16
Selected Model: ARDL(1, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
		Long Run Equation		
LOG(CO2)	-0.661497	0.191170	-3.460253	0.0006
		Short Run Equation		
COINTEQ01	-0.969815	0.032271	-30.05176	0.0000
DLOG(CO2)	0.330990	0.934035	0.354366	0.7232
C	0.622906	0.133114	4.679480	0.0000

Mean dependent var	-0.035518	S.D. dependent var	1.437649
SE of regression	1.032709	Akaike info criterion	2.850584
Sum squared resid	851.0574	Schwarz criterion	3.582621
Log likelihood	-1197.774	Hannan-Quinn criter.	3.129643

*Note: p-values and any subsequent tests do not account for model selection.

Appendix 20.

Model Selection Criteria Table
Dependent Variable: LOG(ACC)
Date: 04/20/21 Time: 02:47
Sample: 2000 2019
Included observations: 940

Model	LogL	AIC	BIC*	HQ	Specification
1	-983.710725	2.993912	3.866822	3.330221	ARDL(1, 1)
2	-941.456354	3.006533	4.168364	3.454156	ARDL(1, 2)
5	-950.368830	3.030236	4.192068	3.477859	ARDL(2, 1)
3	-896.310196	3.011463	4.462216	3.570400	ARDL(1, 3)
6	-904.997278	3.034567	4.485320	3.593503	ARDL(2, 2)
9	-913.838561	3.058081	4.508834	3.617018	ARDL(3, 1)
4	-843.848792	2.996938	4.736612	3.667188	ARDL(1, 4)
7	-856.519042	3.030636	4.770309	3.700886	ARDL(2, 3)
10	-869.085843	3.064058	4.803731	3.734308	ARDL(3, 2)
13	-884.914496	3.106156	4.845829	3.776405	ARDL(4, 1)
8	-803.685060	3.015120	5.043714	3.796683	ARDL(2, 4)
11	-809.295025	3.030040	5.058634	3.811603	ARDL(3, 3)
14	-832.583424	3.091977	5.120572	3.873541	ARDL(4, 2)
12	-755.952799	3.013172	5.330688	3.906049	ARDL(3, 4)
15	-765.748846	3.039226	5.356741	3.932103	ARDL(4, 3)
16	-705.008416	3.002682	5.609118	4.006873	ARDL(4, 4)

Appendix 21.

Algeria

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.105764	0.062963	-17.56224	0.0004
DLOG(CO2)	-15.19554	118.2856	-0.128465	0.9059
C	1.172855	1.289571	0.909493	0.4301

Argentina

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.827465	0.045806	-18.06461	0.0004
DLOG(CO2)	-9.391507	15.69900	-0.598223	0.5918
C	1.394653	0.781730	1.784059	0.1724

Australia

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.093525	0.052089	-20.99356	0.0002
DLOG(CO2)	1.192251	117.4667	0.010150	0.9925
C	1.766598	1.770051	0.998049	0.3918

Austria

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.201360	0.047892	-25.08473	0.0001
DLOG(CO2)	3.037664	27.10199	0.112083	0.9178
C	-0.094987	0.989873	-0.095958	0.9296

Azerbaijan

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.422542	0.151694	-2.785493	0.0687
DLOG(CO2)	-0.839916	14.42575	-0.058223	0.9572
C	0.002587	0.172284	0.015019	0.9890

Belarus

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.876773	0.058704	-14.93547	0.0007
DLOG(CO2)	-4.159031	22.69117	-0.183289	0.8663
C	0.507031	0.520147	0.974786	0.4016

Belgium

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.122939	0.049559	-22.65868	0.0002
DLOG(CO2)	2.850836	27.82901	0.102441	0.9249
C	0.426815	1.155911	0.369245	0.7365

Brazil

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.259477	0.048526	-25.95480	0.0001
DLOG(CO2)	1.380362	5.654690	0.244109	0.8229
C	2.835319	2.444435	1.159908	0.3300

Bulgaria

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.929438	0.114557	-8.113303	0.0039
DLOG(CO2)	2.869948	22.55329	0.127252	0.9068
C	-0.144488	0.570072	-0.253456	0.8163

Canada

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.722526	0.050264	-14.37464	0.0007
DLOG(CO2)	-2.601931	53.12770	-0.048975	0.9640
C	1.068406	0.915491	1.167031	0.3275

Chile

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.274850	0.047013	-27.11703	0.0001
DLOG(CO2)	5.169490	7.421067	0.696596	0.5362
C	0.850623	1.140617	0.745757	0.5099

Hong Kong SAR

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.000455	0.054313	-18.42008	0.0003
DLOG(CO2)	2.957648	6.512560	0.454145	0.6806
C	-0.431948	0.762206	-0.566708	0.6105

Colombia

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.162274	0.050126	-23.18723	0.0002
DLOG(CO2)	3.321386	11.00829	0.301717	0.7826
C	0.675669	0.965089	0.700111	0.5343

Denmark

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.193448	0.040979	-29.12319	0.0001
DLOG(CO2)	-6.656425	13.28741	-0.500957	0.6508
C	-0.768365	0.870870	-0.882296	0.4426

Ecuador

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.934397	0.047788	-19.55310	0.0003
DLOG(CO2)	-0.653943	10.07750	-0.064891	0.9523
C	-0.168106	0.406178	-0.413872	0.7068

Estonia

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.146540	0.051961	-22.06541	0.0002
DLOG(CO2)	0.490569	5.759167	0.085181	0.9375
C	-0.410118	0.508522	-0.806491	0.4790

Finland

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.044638	0.049678	-21.02817	0.0002
DLOG(CO2)	-1.407756	6.593106	-0.213519	0.8446
C	-0.053338	0.714441	-0.074657	0.9452

France

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.076889	0.053159	-20.25779	0.0003
DLOG(CO2)	7.859197	46.54610	0.168848	0.8767
C	1.194383	1.556277	0.767462	0.4987

Germany

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.109440	0.054029	-20.53430	0.0003
DLOG(CO2)	3.590195	124.5389	0.028828	0.9788
C	2.319168	2.338630	0.991678	0.3945

Greece

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.952029	0.051034	-18.65488	0.0003
DLOG(CO2)	-5.724496	63.23034	-0.090534	0.9336
C	0.822562	0.850246	0.967441	0.4047

Hungary

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.023060	0.055096	-18.56873	0.0003
DLOG(CO2)	0.642342	25.06400	0.025628	0.9812
C	0.247119	0.636731	0.388106	0.7238

India

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.943097	0.058759	-16.05022	0.0005
DLOG(CO2)	-1.158709	71.28230	-0.016255	0.9881
C	2.173957	1.993386	1.090585	0.3552

Iran

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.862289	0.059628	-14.46110	0.0007
DLOG(CO2)	-1.622678	52.73613	-0.030770	0.9774
C	1.791139	1.563767	1.145400	0.3351

Ireland

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.129251	0.051417	-21.96263	0.0002
DLOG(CO2)	0.101100	41.61573	0.002429	0.9982
C	-0.555178	0.747058	-0.743153	0.5113

Israel

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.057763	0.075964	-13.92448	0.0008
DLOG(CO2)	-2.875192	17.35489	-0.165670	0.8790
C	0.188638	0.770370	0.244867	0.8224

Japan

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.016802	0.050679	-20.06363	0.0003
DLOG(CO2)	5.107041	36.64440	0.139368	0.8980
C	2.020721	2.176881	0.928264	0.4217

Kazakhstan

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.672602	0.051016	-13.18406	0.0009
DLOG(CO2)	-2.217816	23.81742	-0.093117	0.9317
C	0.992198	0.645782	1.536430	0.2220

Kuwait

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.903505	0.038347	-23.56148	0.0002
DLOG(CO2)	9.137018	11.40622	0.801055	0.4817
C	0.369738	0.685933	0.539029	0.6273

Latvia

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.819285	0.050252	-16.30361	0.0005
DLOG(CO2)	-4.014724	17.05918	-0.235341	0.8291
C	-0.784526	0.230179	-3.408325	0.0422

Lithuania

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.010983	0.056212	-17.98506	0.0004
DLOG(CO2)	1.785197	28.65479	0.062300	0.9542
C	-0.865959	0.353539	-2.449398	0.0917

Morocco

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.336298	0.042470	-31.46426	0.0001
DLOG(CO2)	5.577729	20.44413	0.272828	0.8027
C	-0.614861	1.070441	-0.574400	0.6059

Netherlands

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.264069	0.055243	-22.88195	0.0002
DLOG(CO2)	3.394154	89.89978	0.037755	0.9723
C	0.876508	1.792414	0.489010	0.6584

New Zealand

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.789683	0.050681	-15.58143	0.0006
DLOG(CO2)	1.003091	19.84592	0.050544	0.9629
C	0.138214	0.324721	0.425640	0.6991

Peru

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.962252	0.047064	-20.44554	0.0003
DLOG(CO2)	1.820993	5.899915	0.308647	0.7778
C	-0.091060	0.472591	-0.192682	0.8595

Poland

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.255581	0.048083	-26.11304	0.0001
DLOG(CO2)	9.181069	50.52073	0.181729	0.8674
C	1.405158	1.997333	0.703517	0.5324

Portugal

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.201520	0.048808	-24.61744	0.0001
DLOG(CO2)	2.026516	28.05085	0.072244	0.9470
C	-0.299738	0.933451	-0.321107	0.7692

Romania

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.742434	0.044640	-16.63144	0.0005
DLOG(CO2)	-1.981074	9.164935	-0.216158	0.8427
C	0.462525	0.451040	1.025464	0.3806

Russian Federation

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.721358	0.034196	-21.09477	0.0002
DLOG(CO2)	-19.83218	34.12341	-0.581190	0.6019
C	2.044342	1.339842	1.525808	0.2245

South Korea

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.019981	0.068717	-14.84327	0.0007
DLOG(CO2)	6.050520	99.26330	0.060954	0.9552
C	1.392181	1.702833	0.817568	0.4735

Sweden

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.843321	0.052715	-15.99768	0.0005
DLOG(CO2)	3.856568	31.78891	0.121318	0.9111
C	0.151454	0.468519	0.323262	0.7677

Switzerland

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.724436	0.056987	-12.71233	0.0011
DLOG(CO2)	-4.832662	10.85943	-0.445020	0.6865
C	-0.198026	0.289201	-0.684736	0.5427

Taiwan

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.226409	0.066192	-18.52815	0.0003
DLOG(CO2)	19.18257	128.1339	0.149707	0.8905
C	0.576723	1.791296	0.321959	0.7686

Thailand

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.791777	0.038723	-20.44744	0.0003
DLOG(CO2)	-5.131261	8.495420	-0.604003	0.5885
C	1.661166	0.906698	1.832105	0.1643

Turkey

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.858548	0.056402	-15.22192	0.0006
DLOG(CO2)	-5.184254	80.13718	-0.064692	0.9525
C	0.944192	0.989968	0.953761	0.4106

United Kingdom

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.037864	0.039551	-26.24116	0.0001
DLOG(CO2)	-6.607080	30.20651	-0.218730	0.8409
C	1.363794	1.691084	0.806462	0.4790

United States

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.349008	0.054663	-6.384689	0.0078
DLOG(CO2)	7.244935	32.94436	0.219914	0.8401
C	0.394822	0.496359	0.795435	0.4845

Uzbekistan

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.561364	0.026629	-21.08101	0.0002
DLOG(CO2)	6.814313	25.19343	0.270480	0.8043
C	0.526007	0.328802	1.599769	0.2080

[i] https://www.boldbusiness.com/digital/downside-cryptocurrency-massive-energy-consumption/